Pomelo Fruit Shape Detection and Grading Method Based on Contour Coordinate System Transformation and Fitting (Postprint)

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Abstract

To address the current reliance on manual empirical judgment for pomelo fruit shape and size grading, this study proposes a method employing contour coordinate system transformation fitting, fruit shape feature extraction, and an orientation angle compensation algorithm to detect longitudinal and transverse diameters and identify shape defects based on the fruit shape index. An image acquisition system was constructed using a CMOS camera, dot-matrix LED light source, plane mirror, computer, enclosure, and support frame to obtain full-surface image data of 168 Shatian pomelo samples with varying sizes and shape grades. The G-B component grayscale image was selected for denoising and segmentation. The Laplacian operator edge detection algorithm was utilized to extract fruit edge pixels, and polynomial fitting was employed to transform Cartesian coordinates to polar coordinates, thereby simplifying fruit shape description. Polar angle values of feature points were used to compensate for random sample orientations when calculating longitudinal and transverse diameters by distinguishing between spherical-like and pear-like types. Experiments conducted on Guangdong Meizhou Shatian pomelos demonstrated that the proposed method achieved mean absolute error, maximum absolute error, and mean relative error of 2.23 mm, 7.39 mm, and 1.6%, respectively, for longitudinal diameter, and 2.21 mm, 7.66 mm, and 1.4%, respectively, for transverse diameter. Seven features were extracted from the polar coordinate fitting function of pomelo contours: three peak heights, three peak widths, and one valley value difference. A BP neural network-based discriminant model for pomelo shape was established and validated using an independent validation set, yielding an overall recognition rate of 83.7%. This method provides a rapid non-destructive approach for automated detection and grading of pomelo size and shape.

Full Text

Detection and Grading Method of Pomelo Shape Based on Contour Coordinate Transformation and Fitting

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Abstract: Current pomelo fruit shape and size grading relies heavily on manual judgment. This study proposes a method that detects vertical and horizontal diameters through contour coordinate transformation fitting combined with fruit shape feature extraction and direction angle compensation algorithms, and evaluates shape defects based on fruit shape index. An image acquisition system was constructed using a CMOS camera, dot matrix LED light source, plane mirrors, computer, enclosure, and support brackets to capture complete surface image data of 168 Shatian pomelo samples with varying sizes and shapes. The G-B component grayscale image was selected for denoising and segmentation. The Laplacian edge detection algorithm extracted fruit edge pixels, and polynomial fitting converted rectangular coordinates to polar coordinates to simplify shape description. Characteristic point polar angle values compensated for random sample orientations, enabling separate calculation of vertical and horizontal diameters for spherical and pear-like shapes. Experiments using Guangdong Meizhou Shatian pomelo demonstrated that the proposed method achieved average absolute errors of 2.23 mm and 2.21 mm, maximum absolute errors of 7.39 mm and 7.66 mm, and average relative errors of 1.6% and 1.4% for vertical and horizontal diameters, respectively. Seven features (3 peak heights, 3 peak widths, and 1 trough value difference) were extracted from the polar coordinate fitting function to establish a BP neural network shape discrimination model, which achieved an overall recognition rate of 83.7% when validated with an independent dataset. This method provides a rapid, non-destructive solution for automated pomelo size and shape detection and grading.

Keywords: pomelo contour; fruit shape detection; back propagation neural network; coordinate system conversion; image processing; fruit shape discriminant model

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1 Introduction

Pomelo (*Citrus maxima* (Burm) Merr.) is a major fruit crop in Southeast Asia, rich in nutrients and possessing health benefits. China' s annual pomelo production reaches 3.6 million tons and continues to grow annually [Figure 1: see original paper]. As a large, internally heterogeneous fruit, pomelo shapes vary among cultivars and growing conditions, appearing pear-shaped, near-pear-shaped, spherical, etc. Shape characteristics are typically described by dimensions and proportional relationships among the calyx, neck, shoulder, equator, and apex regions. Common shape defects include excessive neck length, asymmetry, spherical form, and deviation from cultivar-specific characteristics. Current production practices rely on either general-purpose fruit grading equipment based on weight or sieving principles, which cannot fully accommodate pomelo-specific requirements, or on manual grading at orchards based on size and shape, which suffers from high labor intensity, low efficiency, and inconsistent standards. Additionally, most Chinese pomelo cultivation occurs in small-to-medium orchards in hilly mountainous regions with increasing labor shortages and lacking comprehensive postharvest grading technology, severely restricting industry profitability and scale development. Therefore, developing an automated detection and grading method tailored to pomelo fruit shape characteristics is critically important [2].

Machine vision technology offers unique advantages for rapidly and non-destructively acquiring external quality parameters of objects [3], including fruit dimensions, color, and surface defects, which can be combined with feature extraction and processing algorithms for quality assessment. Wang et al. [4] utilized machine vision with principal component analysis and multiple linear regression to establish potato mass and shape grading models by selecting image features with high weight coefficients. Wang et al. [5] employed dual-spore mushroom cap diameter as a size grading parameter, using global threshold segmentation, maximum entropy threshold segmentation, Canny operator, morphological closing, and watershed algorithms to remove shadows and stem interference, then applied minimum enclosing rectangle method to determine cap diameter. Huang and Fei [6] proposed an improved three-layer Canny edge detection algorithm for apple contour extraction and calibrated pixel size using standard rectangular workpieces. Roscher et al. [7] collected natural environment grape images, applied Hough circle detection to identify spherical grapes, and designed classifiers using color and texture information, achieving approximately 1 mm average diameter difference compared to manual measurement with 0.88 correlation and reduced error rates. Oo and Aung [8] simplified strawberry shape to a kite form, identifying four vertices (top, bottom, left, right) and vector angles from fruit boundaries, using vertical distances between vertices as length and lateral point distances as diameter. Arendse et al. [9] employed X-ray computed tomography to generate 2D radiographic images of pomegranate fruits, enabling 3D reconstruction for estimating length, diameter, and peel thickness. These studies estimated fruit shape using diameter, length, and area parameters, while shape features were typically judged manually with cultivar-specific methods, making automated shape detection challenging with limited related research. Common shape discrimination methods include contour extraction and 3D reconstruction. Luo et al. [10] used improved K-means clustering to segment grape images, extracting contour edges and quasi-circular centers to establish a geometric model for separating overlapping grape clusters by solving inflection points at junctions. Wu et al. [11] extracted 2D contour features of jujube to construct 3D multi-contour models for shape detection. Olatunji et al. [12] trained conditional generative adversarial networks on synthetic kiwifruit shape data to reconstruct complete kiwifruit surfaces.

Given pomelo' s asymmetrical characteristics and the overly general description of Shatian pomelo grading standards lacking specific shape parameter criteria, this study proposes acquiring complete surface image information of pomelo fruits and employing contour coordinate transformation fitting combined with direction angle compensation algorithms to detect vertical and horizontal diameters, with shape defects evaluated based on fruit shape index, aiming to provide a rapid, non-destructive solution for pomelo shape detection and grading.

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2 Materials and Methods

2.1 Sample Acquisition

A total of 168 pomelo samples were collected from Meizhou Agricultural Experiment Station and surrounding orchards in Guangdong Province, comprising 81 spherical-shaped, 54 pear-like shaped, and 33 defective samples (lacking Shatian pomelo shape characteristics [13]). Each sample was numbered after manual size measurement and shape classification. For measurement, fruits were clamped between two right-angle plates sliding on horizontal guides along the vertical or horizontal axis direction, with digital calipers measuring each sample twice and averaging the values. Shape classification followed the Shatian pomelo industry standard NY/T 868-2004 [13], categorizing samples into three types through manual observation and measurement of neck length, vertical-to-horizontal diameter ratio, and shape regularity [Figure 2: see original paper].

2.2 Image Acquisition System

Machine vision and image processing technology offer non-destructive, high-compatibility advantages for fruit shape feature extraction and analysis. A custom image acquisition system was constructed [Figure 3: see original paper], primarily comprising an industrial CMOS camera (Taiwan Microscope 1/2.5 MU500, China) with maximum resolution of 2592$\times$1944 pixels, XW0612 lens, image acquisition enclosure (external dimensions 80 cm $\times$ 60 cm $\times$ 60 cm) lined with anti-reflective velvet to eliminate reflection, a 12 W circular LED dot matrix main light source, and adjustable 10 W auxiliary light source. Two opposing plane mirrors inside the enclosure enabled single-shot capture of complete pear-like sample surface information [14]. Based on pomelo size range and preliminary testing, mirror dimensions were set to 30 cm $\times$ 25 cm with 20 cm spacing between adjacent endpoints and 120° mirror angle to ensure complete surface information capture. Samples were placed randomly at the sample position during imaging. The Minte Camera Platform software controlled image acquisition and transferred data via cable to computer for storage and analysis. Sample images obtained by the system are shown in [Figure 4: see original paper].

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3 Feature Extraction and Shape Detection

The technical route for feature extraction and shape detection is illustrated in [Figure 5: see original paper].

3.1 Image Preprocessing

Environmental variations and noise during imaging can obscure image features, necessitating filtering, denoising, and enhancement for subsequent recognition. After comparing mean filtering, median filtering, iterative methods, maximum inter-class variance segmentation, and edge operators (Canny, Sobel, Robert, Laplacian), a color threshold-based segmentation method was adopted. Images were first smoothed using Gaussian filtering to remove noise. In the RGB color model, the G-B chromatic aberration component was selected as the segmentation feature [15,16] [Figure 6: see original paper]. The Otsu method performed binary segmentation on grayscale images, followed by median filtering to remove noise pixels. Morphological opening preserved contour size while filling white holes and gaps. Finally, the Laplacian edge detection operator extracted effective edge information [17-19] [Figure 7: see original paper].

3.2 Contour Coordinate System Transformation

Post-processing contours represent natural shapes with random vertical axis orientation. The curvature variations at the neck and shoulder regions create complex functions in Cartesian coordinates that make principal axis direction determination difficult, increasing computational load and detection errors. Polar coordinates, a 2D coordinate system convertible with Cartesian coordinates, can simplify pomelo contour curve description [20]. Formulas (1) and (2) calculate the centroid coordinates, with the negative X-axis direction selected as the polar axis. In the polar coordinate system, the horizontal axis represents polar angle and the vertical axis represents polar radius, enabling Cartesian-to-polar conversion for contour description [21] [Figure 8: see original paper]. The maximum polar radius peak in the polar coordinate plot determines the offset angle between vertical diameter and horizontal direction. To avoid excessive data volume, fixed-step pixel selection was implemented. [Figure 9: see original paper] compares step sizes m = [10, 20, 30], showing that m = 20 effectively reduced computation while preserving maximal contour information.

3.3 Polar Coordinate Curve Fitting

Curve fitting describes measured data using appropriate functions to analyze variable relationships and extract patterns. This study employed polynomial fitting represented by formula (3). Fitting quality was evaluated using correlation coefficient R and root mean square error RMSE, where higher R and lower RMSE indicate better fit. After coordinate conversion, polynomial fitting was applied to contour data. Table 2 shows fitting results for different polynomial degrees, revealing that when k = 15, R = 0.9714. Increasing k to 17 raised R to 0.9715 with negligible improvement, while RMSE was 0.0190 and computation time was 0.000103 s, satisfying both contour representation and processing speed requirements.

3.4 Vertical and Horizontal Diameter Detection

To improve accuracy and reduce errors, samples were classified as pear-like or spherical. For pear-like pomelo, the vertical axis direction was first determined using the direction angle, then vertical and horizontal diameters were calculated as maximum distances in Y and X directions. For spherical pomelo, minimum enclosing rectangle method was applied. [Figure 8: see original paper] and [Figure 10: see original paper] show contours in both coordinate systems. In polar coordinates, the difference between maximum and second peaks was most significant, thus peak difference ratio CZ was calculated using formula (4). Random sampling of 9 spherical and 9 pear-like samples determined a classification threshold of CZ = 0.34.

For pear-like samples, the maximum polar radius corresponded to the calyx position, enabling polar angle substitution for actual vertical diameter direction angle with average error of 2.55° . Image rotation by this angle yielded vertical-axis-upright contours, with Y and X direction maximum differences representing vertical and horizontal diameters. For spherical samples with small diameter differences, minimum enclosing rectangle method [22] was used: the fruit edge rotated around the centroid through 360°, with the rectangle of minimum area after rotation representing the fruit' s vertical and horizontal diameters.

3.5 Shape Discrimination Model Establishment

Seven features (3 peak heights, 3 peak widths, 1 trough value difference) were extracted from polar coordinate fitting functions to describe pomelo contours [Figure 12: see original paper]. The 168 samples were divided into calibration (119) and validation (49) sets using SPXY method [23], which considers both x and y variables to cover multidimensional space and enhance prediction. BP neural network models were compared with 5-10 hidden nodes and three transfer functions (tansig, logsig, purelin). The optimal structure of 7-6-1 with tansig function achieved 84% accuracy. The input-hidden layer weight matrix (wij) represented connections between nodes, with hidden-output layer weights [-0.6010, 0.6917, 0.3088, -0.5669, -0.8380, -2.2320], hidden layer thresholds [-

1.9280, -2.2626, -0.1841, 0.2974, 1.5112, 1.7438] , and output layer threshold 2.2937 defining the shape index. Classification criteria were: index (-∞, 1.5) = standard shape; [1.5, 2.5) = first-class defect (excessive neck/shoulder); [2.5, +∞) = second-class defect (spherical lacking Shatian characteristics).

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4 Results and Analysis

4.1 Contour Coordinate Transformation and Fitting Results

After coordinate conversion using formulas (1) and (2), polynomial fitting via formula (3) was applied. Table 2 shows fitting results for various polynomial degrees, with k = 15 yielding R = 0.9714. Further increasing k to 17 only marginally improved R to 0.9715 while increasing computational complexity, making k = 15 optimal with RMSE = 0.0190 and processing time = 0.000103 s.

4.2 Pomelo Diameter Detection Results

Manual caliper measurement of 168 samples yielded vertical diameters of 100.10-218.22 mm and horizontal diameters of 88.74-161.36 mm. Image analysis of three views (front, left mirror, right mirror) per sample was performed, with mean values used as final measurements. Table 3 shows detection errors: horizontal diameter average relative error = 1.4%, vertical diameter average relative error = 1.6%.

4.3 Shape Feature Model Establishment and Validation

The BP neural network was trained using 119 calibration samples with initial architecture 7-9-1 (7 input, 9 hidden, 1 output nodes) and learning rate 0.1. Comparative analysis revealed 6 hidden nodes with tansig transfer function achieved optimal 84% discrimination accuracy. The final 7-6-1 network structure with tansig function was established. Validation using 49 samples [Figure 13: see original paper] showed: Class 1 (standard shape, n=29) had 1 false positive and 5 missed detections; Class 2 (minor defects, n=15) had 5 false positives and 2 missed detections; Class 3 (major defects, n=5) had 2 false positives and 1 missed detection. The overall recognition rate was 83.7%.

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5 Conclusion

This study collected complete surface images of 168 pomelo samples, converting Cartesian to polar coordinates to simplify contour description while eliminating orientation effects through direction angle compensation (average error = 2.55°). Size detection achieved average errors of 2.23 mm (vertical) and 2.21 mm (horizontal) with average relative errors of 1.6% and 1.4%, respectively, at processing speeds of 0.000103 s. Seven contour features extracted from polar coordinate fitting curves were used to establish a BP neural network discrimination model (7-6-1 architecture, tansig function) achieving 83.7% overall recognition rate. The results demonstrate that the proposed method enables rapid, non-destructive machine vision-based detection and grading of pomelo size and shape.

Future improvements include: (1) applying additional deep learning algorithms such as support vector machines for shape classification to identify superior methods and improve recognition rates; (2) fusing information from three images (front, left mirror, right mirror) rather than separate discrimination to enhance shape evaluation accuracy.

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