Postprint: Methods for Extracting Phenotypic Parameters of Wheat Plants Based on Three-Dimensional Digitization

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Abstract

To address the challenge that wheat plants have numerous tillers and severe mutual occlusion among organs, making it difficult to accurately extract plant and organ phenotypes from images or point clouds, this study proposes a method for extracting wheat plant phenotypic parameters based on 3D digitization. First, a digital representation method for each organ of wheat plants was proposed, and a 3D digitization data acquisition protocol applicable to the entire growth period of wheat was established and used for data collection. Based on the spatial position semantic information of the 3D digitization data and the definitions of phenotypic parameters, a calculation method for wheat plant phenotypic parameters was proposed, enabling the computation of 11 conventional measurable phenotypic parameters across three categories: length, thickness, and angle of wheat plants and organs. Furthermore, phenotypic indices for quantitatively describing wheat plant architecture and leaf shape were proposed. Among them, plant compactness was calculated by fitting 3D discrete coordinates using the least squares method to quantitatively describe the loose/compact degree of wheat plants; leaf curling and twisting degree of wheat leaves, as quantitative indicators of leaf shape, were calculated based on changes in leaf surface vector directions. Validation was performed using manual measurements and extracted values from three wheat varieties (Fengkang 13, Xinong 979, and Jimai 44) at three growth stages (regrowth, jointing, and heading). The results showed that, while preserving the original 3D morphological structure of plants, the extracted stem length, leaf length, stem thickness, and stem-leaf angle achieved relatively high accuracy compared with measured data, with R^2 values of 0.93, 0.98, 0.93, and 0.85, respectively; the R^2 values for leaf width and leaf inclination angle were 0.75 and 0.73, respectively. This method can conveniently and accurately extract morphological and structural phenotypic parameters of wheat plants and organs, providing effective technical support for wheat phenotypic research.

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Preamble

Phenotypic Traits Extraction of Wheat Plants Using 3D Digitization

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Abstract: Wheat plants exhibit multiple tillers and severe cross-occlusion among organs, making it difficult to accurately extract plant- and organ-level phenotypic traits from images or point clouds. To address this challenge, we propose a phenotypic trait extraction method for wheat plants based on three-dimensional (3D) digitization. First, we developed a digital representation method for wheat organs and established a 3D digitization data acquisition protocol applicable to the entire wheat growth period. Data acquisition was performed according to this protocol. Based on the spatial-semantic information contained in the 3D digitization data and the definitions of phenotypic traits, we propose computational methods for wheat phenotypic parameters, enabling the calculation of 11 conventional measurable traits related to length, thickness, and angle at both plant and organ levels. Furthermore, we introduce quantitative descriptors for wheat shoot architecture and leaf shape. Plant girth, which quantifies the looseness or compactness of wheat plants, is calculated by fitting 3D discrete coordinates using the least squares method. Leaf curling and twisting degrees are defined as quantitative indicators of leaf shape, computed based on variations in leaf surface normal vector directions. Validation was conducted using three wheat cultivars (Fengkang 13, Xinong 979, and Jimai 44) at three growth stages (rising, jointing, and heading), comparing manually measured values with extracted values. Results show that, while preserving the original 3D morphological structure, the extracted stem length, leaf length, stem thickness, and stem-leaf angle achieved relatively high accuracy compared with measured data, with R^2 values of 0.93, 0.98, 0.93, and 0.85, respectively. The R^2 values for leaf width and leaf inclination angle were 0.75 and 0.73, respectively. This method enables convenient and precise extraction of morphological and structural phenotypic parameters for wheat plants and organs, providing effective technical support for wheat phenotyping research.

Keywords: wheat; three-dimensional digitization; visualization; phenotypic traits extraction

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1 Introduction

Plant phenotypes encompass the physical, physiological, and biochemical traits that reflect the structural and functional characteristics of plant cells, tissues, organs, individual plants, and populations. Phenotyping represents the temporal three-dimensional expression of plant genetic maps and constitutes the core content of research on functional-structural plant modeling and digital plant technology. With advancements across disciplines and improvements in data processing capabilities, plant phenotyping has entered the omics era. Traditional measurement methods can no longer meet the high-throughput requirements of plant phenotyping, necessitating accurate and efficient high-throughput phenotyping research tailored to different crops. Wheat is one of the world' s three major food crops, and research on extraction methods for wheat morphological and structural phenotypic traits is crucial for wheat architecture breeding.

Conventional plant morphological phenotyping relies primarily on manual measurements, where accuracy is significantly affected by environmental conditions and human factors. In recent years, image-based plant phenotyping methods have gained widespread application. However, single images cannot resolve complex occlusion problems among plant organs, and the accuracy of some morphological parameter extractions is heavily influenced by image acquisition angles. In contrast, 3D data-based methods can achieve higher precision for plant morphological phenotyping. In wheat 3D phenotyping, Fu et al. used a multi-view image acquisition system to capture wheat seedling images and extracted plant height and leaf length, but only tested wheat before tillering. Zhai utilized LiDAR to obtain 3D wheat data and parsed height and volume traits for biomass modeling. These studies reveal that for crops like wheat with multiple tillers and severe organ occlusion, conventional 2D image and 3D point cloud parsing methods struggle to extract high-precision phenotypic parameters. Moreover, they cannot extract multiple required phenotypic parameters from a single dataset, particularly internal morphological information during later growth stages.

The 3D digitizer is an electromagnetic device capable of measuring precise spatial coordinates of object feature points, making it particularly suitable for plants with complex branching structures. To address the challenge of high-precision phenotyping in plants with extensive cross-occlusion among organs, researchers have used 3D digitizers to directly reconstruct plant architecture in 3D space and extract phenotypic parameters. For example, Wen et al. developed a 3D digitization data acquisition standard for maize based on its morphological characteristics and achieved accurate parsing of maize architecture parameters. Fournier et al. used a 3D digitizer to accurately measure wheat leaf emergence direction, veins, and leaf shape, constructing a dataset for wheat growth and development modeling. However, no reports exist on precise morphological phenotyping of entire wheat plants using 3D digitizers.

Building upon these foundations, this study addresses the morphological characteristics of wheat plants across different growth stages. Using 3D digitization technology, we developed a data acquisition standard for wheat and extracted multiple wheat phenotypic parameters from "plant-tiller-organ" scales in a single, rapid operation while enabling visualization. To enable deeper analysis of wheat 3D morphology, we refined the data acquisition protocol based on previous maize architecture parameter extraction methods to accommodate wheat's complex tiller structure. Compared with skeleton information, the acquired wheat 3D digitization data contains detailed leaf morphology information, enabling extraction of more 3D phenotypic parameters. Additionally, we quantified plant looseness/compaction and leaf curling/twisting degrees. Subsequent 3D reconstruction and phenotyping based on this approach can resolve severe organ occlusion to obtain more accurate and complete information.

2 Wheat Plant 3D Digitization Data Acquisition and Phenotypic Parameter Extraction Methods

Without destroying the original 3D morphological structure, wheat plants were sampled from the field and morphological data were acquired according to the established protocol. After acquisition, the data were visualized for wheat plants at different growth stages using Open3D 0.13.0 in Python 3.8. Simultaneously, relevant phenotypic parameters were automatically extracted, including four categories: height and length parameters, thickness parameters, angle parameters, and leaf curling and twisting degrees. [Figure 1: see original paper] illustrates the overall workflow of wheat phenotypic parameter extraction.

2.1 Wheat 3D Digitization Data Acquisition

2.1.1 Data Acquisition The winter wheat experiment was conducted at the experimental field of the Beijing Academy of Agriculture and Forestry Sciences (N39°56 , E116°16). Three wheat cultivars with distinct differences in architecture and leaf shape were selected: Fengkang 13 (FK13), Xinong 979 (XN979), and Jimai 44 (JM44). FK13 is characterized by tall plants with loose architecture and slender leaves; JM44 has short plants with compact architecture and wide, short leaves; XN979 exhibits intermediate characteristics. Sowing occurred on October 4, 2020. Each cultivar occupied one plot of 2.25 m $\times$ 1.5 m with row spacing of 0.2 m and plant spacing of 0.05 m. Before sowing, compound fertilizer (N-P_2O_5-K_2O: 12-18-15) was applied at 75 g/m^2, and urea was top-dressed at 30 g/m^2 during the jointing stage. Irrigation was applied once during the overwintering period and at jointing, grain-filling, and maturity stages (45 m^3/m^2 each time).

3D digitization data were acquired at three critical growth stages (rising, jointing, and heading) for each cultivar with three replicates. Plants were sampled by transplanting entire individuals into pots and moving them indoors, ensuring intact leaves. Data acquisition was performed on aboveground parts according to the established protocol in a windless environment. Before data collection, position calibration was conducted using a reference block based on electromagnetic positioning principles. Plants were placed within the digitizer' s reachable range. To maintain all organs in a unified coordinate system, plants could not be moved during acquisition. Simultaneously, manual measurements of organ morphological parameters were recorded. During data collection, the instrument could not touch wheat plants to avoid leaf movement-induced errors. After acquiring each plant' s data, a self-developed program was used to visually inspect the data; any missing or erroneous data prompted immediate re-acquisition.

A mechanical arm digitizer Microscribe i (Revware, USA, [Figure 2: see original paper]) was used for data acquisition, with an effective range of 1.27 m and accuracy of 0.178 mm, meeting wheat plant 3D digitization requirements.

2.1.2 Digital Representation of Wheat Plants and Data Acquisition Protocol A data acquisition protocol applicable to the entire growth period was developed based on wheat growth and development patterns to ensure data completeness and correct connectivity among structural units. Cao and Li systematically proposed a sequential naming scheme for aboveground wheat organs using English initials and numerical markers to indicate spatiotemporal positions. Building upon this organ-based structural unit division, we developed a digital representation method and data acquisition protocol for wheat organs.

(1) Stem. Represented by S (Stem). The main stem is S_M; tillers are S_{Ti},j, where i is the primary tiller number attached to the main stem and j is the secondary tiller number attached to the primary tiller. Tertiary tillers were not considered due to low survival rates. First, three coordinate points were acquired circumferentially at the stem emergence point to record thickness information. Then, points were acquired from the stem base upward ([FIGURE:3(a)]), ending at the connection point between the last leaf and the stem. After jointing, each point was required to coincide with wheat nodes. After heading, the emergence point of the ear served as the endpoint. The main stem data point set is denoted as {S_M^k}, where N_{SM} is the number of acquired main stem points (0 < k ≤ N_{SM}, k). The main stem emergence point S_M^4 is considered the plant' s origin. Tiller data point sets are denoted as {S_{Ti},j^k}, where N_{STi},j is the number of points for the corresponding tiller.

(2) Leaf. Represented by L (Leaf). Main stem leaves are L_M; tiller leaves are L_{Ti},j. Data were acquired row-by-row from the leaf emergence point toward the tip, capturing three points per row: left edge, midrib, and right edge ([FIGURE:3(b)]), ending with a single point at the leaf tip. The interval distance should not be too long and must include points representing obvious morphological changes and the leaf' s highest point. When leaves were twisted, data acquisition followed the initial transverse direction after virtual flattening. The main stem leaf data point set is denoted as {L_M,n^k}, where n is the leaf development sequence, Q_0 is the number of leaves on the main stem (0 < n ≤ Q_0, n), and N_{LM}^n is the number of points for the nth main stem leaf. Tiller leaf data point sets are denoted as {L_{Ti},j,n^k}, where Q_i,j is the number of leaves on the corresponding tiller and N_{LT}^i,j,n is the number of points for the nth leaf.

(3) Ear. Represented by E (Ear). The main stem ear is E_M; tiller ears are E_{Ti},j. Data acquisition started from the ear emergence point and proceeded upward, ending at the ear tip. The main stem ear data point set is denoted as {E_M^k}, where N_{EM} is the number of points (0 < k ≤ N_{EM}, k). Tiller ear data point sets are denoted as {E_{Ti},j^k}, where N_{ETi},j is the number of points for the corresponding tiller ear.

2.2 Phenotypic Parameter Extraction Methods

2.2.1 Data Standardization Before visualization and phenotypic parameter extraction, 3D digitization data must be standardized to position wheat plants at the origin with the main stem growing vertically upward and aligned with the Z-axis, facilitating visualization and height parameter calculation.

Since the first three points in the main stem data set represent thickness information and the fourth point S_M^4 is the main stem emergence point, S_M^4 is first translated to coordinates (0,0,0) with all remaining points undergoing the same translation. The plant is then rotated according to the main stem growth direction, represented by the vector formed between the first and last points recording length information on the main stem (g). Let v_z = (0,0,1) be the unit vector along the positive Z-axis. The angle between g and v_z is calculated, and all data points are rotated around axis = g × v_z by angle to complete standardization. After standardization, the Z-coordinate represents height information.

2.2.2 Length Parameter Extraction **(1) Plant height, stem length, and internode length calculation.** According to the acquisition protocol, stem data points coincide with nodes after jointing. Let d(p_i, p_j) denote the Euclidean distance between two points in 3D space. For the main stem, the length of the ith internode is calculated as:

$$\text{node}_i = d(S_M^{i+3}, S_M^{i+4}), \quad 1 \le i < N_{SM} - 3 \tag{1}$$

Stem length is the sum of all internode lengths:

$$s = \sum_{i=1}^{N_{SM}-3} \text{node}_i \tag{2}$$

After standardization, the Z-coordinate represents height. Plant height is the maximum height among the main stem and all tillers. Before heading, the maximum height is determined by the Z-coordinate of the uppermost leaf tip. Let N_{LM}^{Q_0} be the number of points on the main stem' s uppermost leaf, with n_0 = N_{LM}^{Q_0}, then L_M^{Q_0,n_0} is the last point of the main stem' s uppermost leaf. Let N_{LT}^{i,j,Q_i,j} be the last point of tiller T_i,j' s uppermost leaf, with n_i,j = N_{LT}^{i,j,Q_i,j}, then L_{Ti},j^{Q_i,j,n_i,j} is the last point of the tiller' s uppermost leaf. Plant height H is calculated as:

$$H = \max(L_M^{Q_0}.z, \max(L_{Ti,j}^{Q_i,j}.z)) \tag{3}$$

After heading, the maximum height depends on flag leaf orientation, selecting the larger Z-coordinate between the flag leaf tip and ear tip. Let E_M^{N_{EM}} be the last point of the main stem ear and E_{Ti},j be the last point of tiller ears. Plant height is then:

$$H = \max(L_M^{Q_0}.z, \max(L_{Ti,j}^{Q_i,j}.z), E_M^{N_{EM}}.z, \max(E_{Ti,j}.z)) \tag{4}$$

(2) Leaf length, leaf width, and leaf emergence position calculation. The interval distance between leaf data rows ensures no large curvature changes, so leaf length is calculated by summing distances between adjacent midrib points. However, the polyline accumulation underestimates actual leaf length, requiring an empirical scaling factor determined from actual vs. extracted values for different cultivars. With midrib point intervals of 3 and the final tip interval of 2, leaf length for the main stem' s first leaf (with point set size N_{LM}^1) is:

$$l = \left(d(L_M^{1,1}, L_M^{1,2}) + \sum_{i=1}^{(N_{LM}^1-2)/3} d(L_M^{1,3i}, L_M^{1,3i+2}) \right) / \xi \tag{5}$$

Leaf width is the sum of distances from left/right edge points to the midrib point, with empirical factor τ determined similarly. For the main stem' s first leaf at the ith row:

$$w_i = \left(d(L_M^{1,3i-1}, L_M^{1,3i}) + d(L_M^{1,3i}, L_M^{1,3i+1}) \right) / \tau \tag{6}$$

Maximum leaf width w_{max} is max(w_i). Leaf emergence position is the connection point between leaf and stem, specifically the midrib point of the first data row (L_M^{1,1}), with emergence height L_M^{1,1}.z.

(3) Ear length and ear emergence position calculation. Ear length is similarly calculated by summing distances between adjacent ear points. For the main stem:

$$e = \sum_{i=1}^{N_{EM}-1} d(E_M^i, E_M^{i+1}) \tag{7}$$

Ear emergence position is the first coordinate point in the ear data set (E_M^1), with emergence height E_M^1.z.

2.2.3 Thickness Parameter Extraction (1) Stem thickness calculation. Stem thickness is determined by calculating the circumradius of the first three stem points. Using the constraints of three-point coplanarity and equal distances to the circumcenter, three plane equations are constructed:

$$AP + B = 0 \tag{8}$$

where A is a 3$×$3 coefficient matrix, B is a constant vector, and P is the circumcenter coordinate matrix. For the main stem, circumcenter p_o (x_o, y_o, z_o) is calculated from points S_M^1, S_M^2, S_M^3. Stem thickness o is twice the weighted average distance from these three points to the circumcenter:

$$o = \frac{2}{3}\sum_{i=1}^{3} d(S_M^i, p_o) \tag{9}$$

(2) Plant girth calculation. Wheat plant compactness/looseness directly relates to lower stem growth after tillering. Plant girth is defined as the diameter of the circumscribed circle formed by all stems at the lower 1/3 plant height. For a plant with height H, m stem coordinate points p_i at H/3 height are fitted. Since points don' t lie exactly on a circle, the Lagrange multiplier method is used to solve for the optimal circle center [24]. The Lagrangian function F(P_u, λ) is constructed, and first-order partial derivatives are set to zero to solve for optimal center coordinates P_u = [[x_u, y_u, z_u]]^T:

$$F(P_u, \lambda) = \|DP_u - G\|^2 + \lambda(UP_u - 1) \tag{10}$$

where D and G are m$×$3 matrices and constant terms from linear equations f(x_u, y_u, z_u) constructed using the property that any two-point connection is perpendicular to the line connecting the midpoint and center; U = ((a, b, c))^T contains plane coefficients ax + by + cz = 1 for all discrete points.

Plant girth u is determined by twice the weighted average distance from each stem point p_i to center p_u (x_u, y_u, z_u):

$$u = \frac{2}{m}\sum_{i=1}^{m} d(p_i, p_u) \tag{11}$$

2.2.4 Angle Parameter Extraction **(1) Stem-leaf angle calculation.** Following the definition and manual measurement method, the stem-leaf angle is calculated as the angle between two spatial vectors: leaf emergence direction and local stem direction. Leaf emergence direction l is represented by the first two midrib points, while local stem direction s is the internode vector containing the leaf emergence height. The stem-leaf angle α is:

$$\alpha = \arccos\left(\frac{l \cdot s}{\|l\| \cdot \|s\|}\right) \tag{12}$$

(2) Leaf inclination angle calculation. Typically, leaf inclination angle is measured between the vector connecting the leaf collar to tip and the XOY plane. However, wheat leaves show large variations across growth stages with significant bending, requiring segmented calculation. According to the acquisition protocol, the leaf highest point must be included in the data set. The angle between adjacent midrib vectors and the XOY plane is calculated, with the average of valid segments as the final result ([Figure 5: see original paper]). Segments after the highest point and those showing drooping due to gravity or senescence are excluded. For the main stem' s first leaf with N_{LM}^1 points, assuming m valid segments before the highest point, the first midrib vector' s projection on XOY plane is v_1. The leaf inclination angle β is:

$$\beta = \arccos\left(\frac{\sum_{i=1}^{m}(L_M^{1,3i+2} - L_M^{1,3(i-1)+2}) \times v_1}{\|\sum_{i=1}^{m}(L_M^{1,3i+2} - L_M^{1,3(i-1)+2})\| \cdot \|v_1\|}\right) \tag{13}$$

2.2.5 Leaf Curling and Twisting Parameter Extraction During wheat growth, some leaves undergo twisting and curling deformations. Quantifying these through parameters facilitates analysis of leaf morphology differences among cultivars.

(1) Leaf curling degree calculation. Leaf curling quantifies the curvature formed by left and right leaf surfaces centered on the midrib. Surface normal vectors u_{left} and u_{right} for left/right leaf facets are calculated using the right-hand rule, and their included angle γ determines curling degree at that leaf position ([Figure 6: see original paper]). For the main stem' s first leaf with N_{LM}^1 points, (N_{LM}^1)/3 midrib-left/right facet angle pairs are determined. Curling degree c is:

$$c = \frac{1}{(N_{LM}^1 - 1)/3} \sum_{i=1}^{(N_{LM}^1-1)/3} \frac{\gamma_i}{90} \tag{14}$$

c ranges in [0,1], with larger values indicating more severe curling.

(2) Leaf twisting degree calculation. Leaf twisting quantifies the overall directional change along the midrib from base to tip. For untwisted leaves, vectors formed by corresponding left/right edge points should be parallel in 3D space. Twisting degree is determined by the cumulative sum of angles between adjacent vectors ([Figure 7: see original paper]). For the main stem' s first leaf with N_{LM}^1 points, (N_{LM}^1)/3 vectors are determined:

$$v_i = L_M^{1,3i} - L_M^{1,3i-2}, \quad 1 \leq i \leq (N_{LM}^1)/3 \tag{15}$$

Twisting degree q is calculated as:

$$q = \frac{1}{360} \sum_{i=2}^{(N_{LM}^1)/3} \arccos\left(\frac{v_i \cdot v_{i-1}}{\|v_i\| \cdot \|v_{i-1}\|}\right) \tag{16}$$

q ranges in [0,1], with larger values indicating more severe twisting. [Figure 8: see original paper] visualizes wheat leaves with twisting degrees of 0.12, 0.56, and 0.89.

2.3 Data Visualization

The Open3D library processes and visualizes wheat plant data through three steps:

(1) Triangular meshing. Using the coordinate and sequential information in digitization data, triangular meshes are generated.

(2) Mesh subdivision. The Loop subdivision method [25] is applied to refine leaf meshes, with two iterations achieving optimal results for wheat leaves.

(3) Mesh coloring. The paint_{uniform}_{color} function colors meshes according to wheat organ colors.

[Figure 9: see original paper] shows the visualization pipeline for a single leaf and whole plant: original digitization data, triangular meshing, mesh subdivision, and colored mesh.

2.4 Data Analysis Methods

The following criteria evaluate parameter accuracy:

(1) Root Mean Square Error (RMSE) measures the average error between measured and predicted values:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(\text{actual}_i - \text{predicted}_i)^2}{n}} \tag{17}$$

(2) Coefficient of determination (R^2) measures model fit between measured and predicted values, ranging in [0,1]:

$$R^2 = \frac{\sum_{i=1}^{n}(\text{predicted}_i - \text{Mean})^2}{\sum_{i=1}^{n}(\text{actual}_i - \text{Mean})^2} \tag{18}$$

where Mean is the average of measured values:

$$\text{Mean} = \frac{\sum_{i=1}^{n} \text{actual}_i}{n} \tag{19}$$

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3 Results

3.2 Parameter Extraction Accuracy Analysis

To evaluate the accuracy of the proposed method, data from the rising, jointing, and heading stages were validated. Since other methods cannot precisely extract required phenotypic parameters for all growth stages, manual measurements were used for comparison. presents mean extracted and measured values for length, thickness, and angle parameters at heading stage for three cultivars. Results show small differences between extracted and measured values, with cultivar differences clearly reflected. FK13 shows maximum leaf length and minimum leaf width; JM44 has relatively small leaf length but maximum leaf width; XN979 is intermediate. For stem traits, FK13 has long, thin stems; XN979 has short, thick stems; JM44 is intermediate. FK13 shows larger stem-leaf angles but smaller leaf inclination angles; JM44 shows the opposite; XN979 is intermediate.

[Figure 10: see original paper] displays visualization results for the three cultivars at three growth stages. JM44 has the most tillers, followed by XN979, then FK13. For plant architecture, XN979 is relatively taller before jointing, but FK13 internodes elongate rapidly after jointing, making it the tallest at final morphology. FK13 also shows larger girth values, indicating looser architecture, while XN979 and JM44 are more compact. For leaf morphology, FK13 leaves are slender with maximum leaf length, minimum leaf width, and greater curling; XN979 and JM44 have larger leaf widths with less curling; JM44 shows greater leaf twisting due to cultivar characteristics, while XN979 leaves are the flattest.

[Figure 11: see original paper] compares extracted vs. measured values for leaf length, leaf width, stem length, stem thickness, stem-leaf angle, and leaf inclination angle across three growth stages, showing RMSE and R^2. Pink, black, and blue represent rising, jointing, and heading stages, respectively.

Other methods cannot completely and accurately obtain wheat phenotypic parameters while preserving original 3D morphology, especially during key growth stages after the three-leaf stage when wheat architecture becomes complex and organ occlusion is severe. Comparison results show small errors for leaf length, stem length, stem thickness, and stem-leaf angle, with average R^2 values of

0.93, 0.98, 0.93, and 0.85, respectively. Leaf width and leaf inclination angle R^2 values are 0.75 and 0.73, respectively. Without destructive measurement, these errors are acceptable.

3.3 Parameter Extraction Time Efficiency Analysis

To evaluate reconstruction efficiency, CPU time for single-plant data processing and parameter extraction was measured. For heading-stage wheat with average 7 tillers and 27 leaves, data reading and processing took ~121 ms, while parameter extraction took ~12 ms, totaling ~133 ms. The method was implemented in VS2019 on Windows 10 using an Intel(R) Core(TM) i7-10700 CPU @ 2.90GHz with 16GB RAM.

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4 Discussion

This study developed a rapid, accurate, and automated method for wheat phenotypic parameter extraction addressing wheat’ s multiple tillers and severe organ occlusion. The method features strong consistency, high precision, and convenient operation. While preserving original 3D morphology, it visualizes wheat 3D digitization data and simultaneously calculates 11 conventional measurable phenotypic parameters across length, thickness, and angle categories. Additionally, it quantifies plant looseness/compaction and leaf curling/twisting, better characterizing wheat morphology at plant and organ scales. This facilitates analysis of morphological differences among wheat cultivars and supports ideal plant type breeding.

The established protocol incorporates semantic information, using 3D digitization to precisely locate spatial positions of stems, leaves, ears, and other organs, solving organ occlusion problems and enabling accurate phenotypic parameter extraction. This protocol can be directly applied to Poaceae crops with similar morphology like rice, and can be adapted for other crops.

The method enables quantitative measurement of parameters like plant girth, leaf curling, and twisting that are difficult to measure manually. While manual measurement workload is similar to 3D digitization for a single plant, digitization provides objective data unaffected by subjective factors or reading habits, ensuring better consistency.

Image-based and 3D point cloud-based plant architecture parameter extraction are widely used for crops like maize, cotton, and sugar beet. However, wheat’ s multiple tillers, numerous slender leaves, and severe mutual occlusion make these methods unsuitable for entire growth periods, with limited extractable parameters. No other methods can automatically batch-extract all wheat phenotypic parameters included in this system without destroying original 3D morphology. In existing wheat phenotyping studies, multi-view image systems combined with Mask R-CNN extracted wheat leaf length and plant height with R^2 of 0.87 and

0.98, respectively. Our method achieved R^2 of 0.93 and 0.98 for leaf length and stem length, respectively, with smaller errors. LiDAR-based methods estimated wheat tiller numbers with R^2 of 0.61 and 0.56 across two years and built biomass models using height and volume, but lacked more precise length and angle parameters. Our method directly obtains tiller numbers from data set counts and extracts length, thickness, and angle parameters with R^2 values of 0.93, 0.98, 0.93, and 0.85 for leaf length, stem length, stem thickness, and stem-leaf angle, respectively. Leaf width and leaf inclination angle R^2 values are 0.75 and 0.73, respectively—slightly larger errors than other parameters due to narrow wheat leaves that curl and twist, causing edge points to deviate from perpendicular positions relative to the midrib. Manual leaf width measurement is also challenging for determining maximum width position. Larger leaf inclination angle errors result from inconsistent manual measurement positions; our method calculates means from multiple extraction points, achieving higher precision for various leaf curvatures.

This study also achieved wheat plant visualization and simulation, completely restoring 3D morphology for accurate organ-scale phenotyping. Although rapid wheat 3D reconstruction has been reported, point clouds from 3D scanning or multi-view reconstruction suffer from missing leaf edge and internal plant information, making them unsuitable for complex plants and limiting high-precision organ-scale parameter extraction. Our method provides accurate data but relies on equipment with relatively high time costs, requiring further research for high-throughput wheat phenotyping.

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