

Knitted Fabric Pattern Design Based on Three-Dimensional Data Graphic Generation Algorithms

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Abstract: In the field of contemporary textile pattern design, floral patterns are widely favored due to their diversity and aesthetic appeal. However, due to the wide variety of flowers and their complex morphological structures, accurately presenting their characteristics and aesthetic appeal through computer-aided design techniques, such as 3D modeling, poses certain challenges. Based on this, the study proposes a graphic editing algorithm that combines 3D data with a directional bounding box method. On this basis, a textile pattern design system is established. The results show that the proposed algorithm performs exceptionally well. Experimental results on the Oxford 102 Flower Dataset indicate that the proposed algorithm achieves a mean squared error of 0.25, a root mean squared error of 0.001, and a mean absolute error of 0.0017. In addition, the method for extracting contour sampling points based on the front and side angles of flowers maintains flower contour integrity over 85% throughout the experimental process, reaching 100% at most. These findings suggest that the proposed method can comprehensively capture flower-contour information and generate two-dimensional design drawings with high accuracy, thereby improving the efficiency of textile pattern design.

Keywords: 3D modeling, graphics generation algorithm, oriented bounding box (OBB), weave pattern design, system design.

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1. Introduction

Floral woven fabrics, with their rich patterns and diverse structures, have found widespread application in various areas of daily life. In the design of such fabrics, drawing flower-pattern concept sketches is a crucial step (Wu et al., 2021). Traditional flower pattern design requires professional designers to work manually, which is not only time-consuming and labor-intensive but also poses challenges for those lacking an artistic background in creating beautiful concept sketches (Zhu et al., 2021). With advances in computer technology, the design of knitted jacquard fabrics has begun to shift towards automation and customization. By using computer technology to transform designers' creativity into 3D models at the early design stage and to automatically generate 2D concept sketches, the need for manual drawing can be eliminated, thereby enhancing production efficiency (Fang et al., 2021). This method not only improves the convenience of design work but also provides new possibilities for innovative design of weft-knitted jacquard fabrics. However, for objects such as flowers, which are diverse and have complex, variable structures, it is difficult to represent them using 3D modeling (Junior et al., 2022). Therefore, how to complete the 3D reconstruction of flowers in a relatively short time and utilize it in the design process for weaving concept sketches has become an urgent technical challenge (Kazancoglu et al., 2020). To address this issue, the study examines the accuracy and efficiency of automatically generated design sketches. The study first analyzes current advanced image-generation technology and then examines the automation status of modern weaving design.

The method proposed in this study involves image generation. At present, two-dimensional image generation technology has become increasingly mature and has achieved remarkable results in many fields. Shrestha et al. (2020) found that machine learning supports the inductive process in the Social Sciences and helps identify replicable data patterns to build theories and quickly generate reasoning diagrams. Beyan et al. (2023) explored the application of an artificial intelligence image generator in architectural design, and the results showed that it could inspire designers through a variety of visual schemes.

Modern textile pattern design uses digital tools such as CAD to improve efficiency. Pietroni et al. (2022) proposed an automatic sewing pattern generation algorithm for 3D clothing that accounts for seam symmetry, darts and fabric anisotropy.

Meng et al. (2020) proposed an automatic yarn positioning and pattern recognition method that achieved high-precision positioning and improved production efficiency.

In summary, numerous researchers have conducted extensive studies on image generation and intelligent weaving technologies, yielding notable results. However, the existing technology has the following problems: Firstly, the process lacks adaptability, creating a gap between pixels and fabrics; Secondly, textile patterns need to balance aesthetics and functionality, but image generation technology tends to produce more detailed, highly complex patterns. Based on this, the study proposes a method that combines a 3D data-driven graphic editing algorithm with an Oriented Bounding Box (OBB) to build a woven fabric pattern design system. The aim of the study is to complete the 3D reconstruction of flowers in the shortest possible time and apply it to the design process of weaving art patterns, thereby achieving high efficiency and precision in weaving design. The contribution of the study lies in optimizing the design and production process, enabling faster response to market changes and meeting consumers' demands for personalized and customized products. The innovation of the study lies in proposing a new 3D modeling method for the complexity of floral patterns in weaving design. This method can handle the diversity and complex structure of flowers, enabling a 3D representation. In addition, by combining OBB technology, the study provides a new method for estimating spatial range. From a theoretical perspective, research provides a formal descriptive framework for dealing with textile pattern objects that have complex, irregular shapes. In addition, the research has clarified the technical path from front- and side-profile sampling to grid construction and then to two-dimensional pattern generation, enriching the theoretical application scenarios of computer-aided design for textile patterns.

2. Methods and Materials

2.1. Model Construction of Woven Fabric Patterns from both Front and Side Perspectives

In the design of knitted apparel, floral patterns are favored by consumers for their diversity and aesthetic appeal, often serving as the theme for jacquard designs (Sanaat et al., 2021). Given the wide variety and complex shapes of flowers in nature, converting floral patterns into three-dimensional models and realizing intelligent generation of floral patterns will greatly enhance the efficiency of designing floral patterns (Chang, 2021). To ensure that the model accurately reflects the object from different angles, it is necessary to meticulously construct each part of the object (Umair et al., 2020). In a three-dimensional view, objects may occlude one another, so before modeling, the study needs to extract sampling points from the flower image's contours. The extraction of contour sampling points for the flower is shown in Fig. 1.

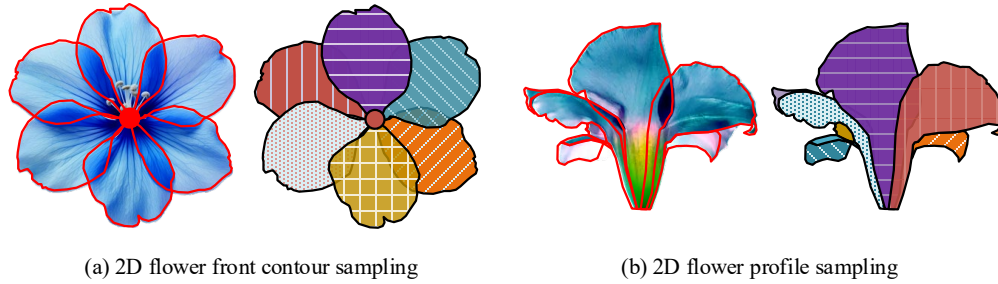


Fig. 1. Extraction of sampling points for the front and side contour of two dimensional flowers

As shown in Fig. 1, the occlusion of the front and side flowers varies with perspective. The study uses the flower's three-dimensional central axis as a reference to determine the tilt angle of each petal, and the calculation is given in Eq. (1).

$$\theta = \arctan \left(\frac{|P_{top_y} - P_{d_y}|}{|P_{top_x} - P_{d_x}|} \right) \quad (1)$$

In Eq. (1), P_{top_y} and P_{top_x} represent the highest points of the petals in the y-axis and x-axis directions, respectively, while P_{d_y} and P_{d_x} represent the first sampling points on the y-axis and x-axis sides of the central axis curve, respectively. Since flower petals often do not grow uniformly, complex-patterned petals are required as design support in weaving and embroidery. In 3D modeling, handling the grid layout of irregular petals is challenging (Hunter et al., 2023; Yao et al., 2021). To address this, a method is proposed to segment the 2D contour of irregular petals into curves and generate petal grids by computing both front and side angles. This method first requires establishing the center point of each petal, as shown in Eq. (2).

$$P_c = \frac{\sum_{i=1}^n P_i}{n} \quad (2)$$

In Eq. (2), P_c represents the center point of a single petal, P_i represents the coordinates of the i th sampling point on a single petal, and n represents the sum of the number of sampling points on the left and right contour lines of a single petal. From this, the direction vector of a single petal can be calculated, as shown in Eq. (3).

$$V = \frac{P_c - P_m}{L_{cm}} \quad (3)$$

In Eq. (3), V represents the direction vector of a single petal, P_m represents the midpoint between the endpoints of the left and right contour lines of a single petal, and L_{cm} represents the magnitude of the vector P_c and vector P_m . Based on the above Eq.s, the contour coordinates of the tip of a single petal can be calculated, as shown in Eq. (4).

$$C_{i_z} = P_{L_z} + d_i \cdot \tan\theta \quad (4)$$

In Eq. (4), C_{i_z} represents the z coordinate of the second-dimensional contour point of the i th flower tip, P_{L_z} represents the z coordinate value of the left turning point, and d_i represents the distance from the i th two-dimensional contour point of the flower tip to the left contour line P_L and the right contour line P_R of the petal. After completing the above steps and obtaining the contour data on both sides of each petal, the initial grid for building the petal model is shown in Fig. 2.

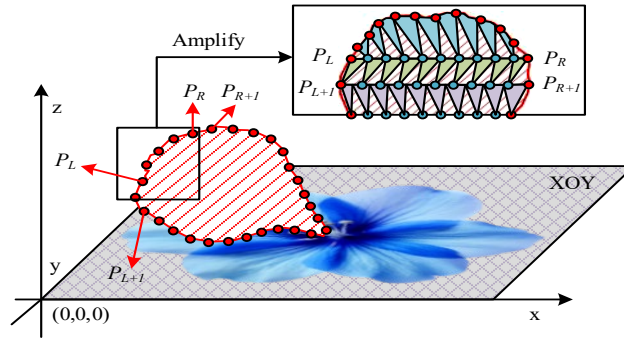


Fig. 2. Initial grid for building a petal model in research

In Fig. 2, P_L and P_{L+1} represent two points on the left contour line of the petal, while P_R and P_{R+1} represent points on the right contour line of the petal that are symmetrical to the left contour. It can be observed that, to make the mesh of the petal model conform to the petal's irregular tip shape, the study evenly divides the line segments P_L and P_R into n small segments at the petal tip. In terms of mesh wiring, the study selects every third vertex in order from left to right and then connects them counterclockwise to form triangular patches, as shown in the enlarged view of Fig. 2. This triangular-symmetric connection method facilitates deformation of the flower model mesh.

2.2. Three-Dimensional Data Graph Generation Algorithm

A complete weave pattern design often encompasses a diverse array of patterns. Therefore, after initially establishing the flower grid model in the previous section, further research was conducted into the diversification of weave patterns. Unlike two-dimensional images, three-dimensional object images can be manipulated through scaling, rotation, and replication, ultimately resulting in a complete and rich weave pattern (Keune 2022; Han et al., 2023). Based on this, a graphic editing algorithm based on three-dimensional data was proposed. This method includes converting a three-dimensional model into a two-dimensional image, which requires users to understand the basic principles of object projection. The types of projections mapped onto a two-dimensional plane mainly include parallel, oblique, and orthographic projections. The three projection methods are shown in Fig. 3 (Krishnamurthy et al., 2021).

As shown in Fig. 3(a), parallel projection is the case in which light rays are incident on an object in parallel and then projected onto a plane. This type of projection is commonly used in technical drawing (Arada et al., 2023). In Fig. 3(b), oblique projection is also considered a type of parallel projection, in which one face of the object is parallel to the projection plane, while the other faces are projected at an angle (Keune et al., 2021). In Fig. 3(c), orthographic projection is the projection of an object perpendicular to the projection plane. In this type of projection, the distances from all points on the object to the projection plane are equal, so the object's size does not change with distance (Chantamool et al., 2024). After mastering the projection of model grids, the research then proceeds to constrain the deformation and encoding of the flower model. The coordinate-positioning calculation for a given point in the flower model is given by Eq. (5).

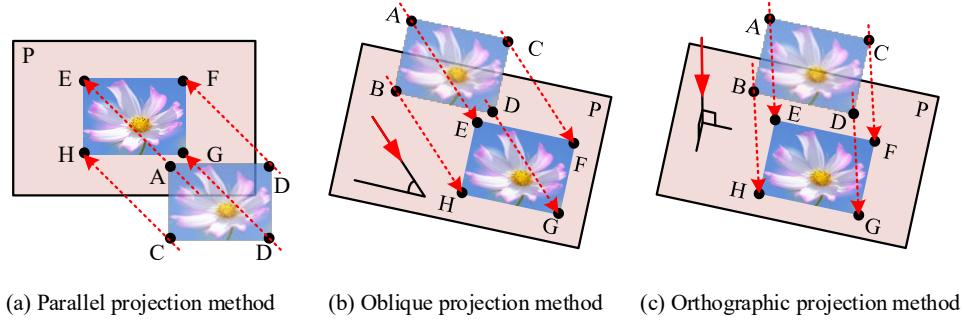


Fig. 3. Three projection methods for 3D rendering and 2D rendering

$$Z_i = \sum_{j \in N(i)} w_{ij} (v_i - v_j) \quad (5)$$

In Eq. (5), Z_i represents the coordinates of the point i in the flower model. $N(i)$ represents the set of all vertices that form edges with point i . v_i and v_j represent point i and point j in the flower vertex set. w_{ij} represents the uniform weight between point i and point j . When the flower model undergoes deformation, the displacement of a given vertex is given by Eq. (6).

$$y_i = d_i \cdot \sin(\pi \cdot \frac{i}{t}) \quad (6)$$

In Eq. (6), y_i represents the distance that the flower needs to move to reach the ideal level, d_i represents the amplitude of the sine function of the distance, and t represents the total number of vertices that need to be moved. From this, the coordinates of the center point of the flower model after deformation or movement can be deduced, as calculated in Eq. (7).

$$P_i = P_1 P_N \cdot y_i + P_{init} \quad (7)$$

In Eq. (7), P_i represents the coordinate point of the flower after reaching the ideal degree of movement, P_N represents the center point on the petals of the flower model, P_1 represents the petal mid-axis vector, and P_{init} represents the coordinate point before deformation or movement. The petal roots of natural flowers do not grow in a straight line but exhibit a staggered pattern (Tucci et al., 2021). Therefore, when designing a graphic editing algorithm based on three-dimensional data, the natural state of the petals is also taken into account to avoid model penetration. To reduce computational load, the study groups each petal and uses the OBB method to quickly estimate the spatial extent of the flower model and control the degree of collision contact for each model. OBB can be understood as a bounding box aligned with the object's direction, which is no longer limited to coordinate-axis alignment, thereby enabling it to more closely surround point clouds or objects (Mandorli et al., 2021; Otto et al., 2022). The study uses the flower model to generate the center control points for the OBB petal bounding box, as shown in Eq. (8).

$$O_c = \frac{1}{3m} \sum_{i=1}^n (p^i + q^i + r^i) \quad (8)$$

In Eq. (8), O_c represents the center control point of the petal bounding box. m represents the total number of mesh patches in the petal. p^i , q^i and r^i represent the vertices of triangular mesh patches. In summary, the flower OBB model, which incorporates 3D data and graphic editing algorithms, is shown in Fig. 4.

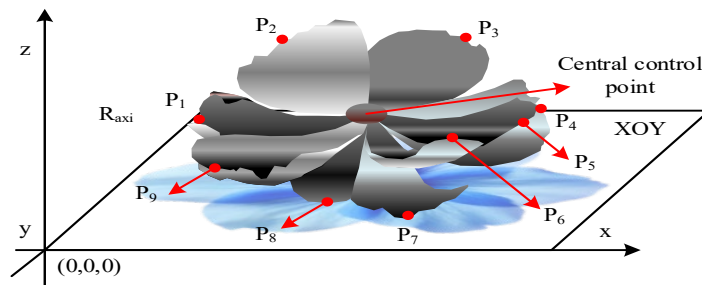


Fig. 4. Flower OBB model based on graphic editing algorithm combined with 3D data

As shown in Fig. 4, when modeling multi-layered interlaced flowers, each petal is represented by an independent OBB bounding box, facilitating model decomposition. Firstly, the number of petal layers is extracted based on the central axis curve of the flower, and then the left and right contour curves of each individual petal are extracted. The combined flower is built from the top down. In addition to replication and combination, the model can also be scaled and translated. Through this grouping method, other flower combinations can be freely created (Weeks et al., 2023). The translation change of the flower model is calculated as shown in Eq. (9).

$$\begin{pmatrix} x_{new1} \\ y_{new1} \\ z_{new1} \\ 1 \end{pmatrix} = \begin{bmatrix} 1 & 0 & 0 & -x_{O_1} \\ 0 & 1 & 0 & -y_{O_1} \\ 0 & 0 & 1 & -z_{O_1} \\ 0 & 0 & 0 & 1 \end{bmatrix} \cdot \begin{pmatrix} x \\ y \\ z \\ 1 \end{pmatrix} \quad (9)$$

In Eq. (9), x_{new1} , y_{new1} , and z_{new1} represent the coordinates of the three-dimensional midpoint of the flower model after translation, x_{O_1} , y_{O_1} , and z_{O_1} represent the coordinates of the flower's center O_1 , and y , x , and z represent the coordinates of the three-dimensional midpoint of the flower model before translation. From this, the calculation Eq. for the scaling change of the flower model can be deduced, as shown in Eq. (10).

$$\begin{pmatrix} x_{new2} \\ y_{new2} \\ z_{new2} \\ 1 \end{pmatrix} = \begin{bmatrix} m & 0 & 0 & 0 \\ 0 & m & 0 & 0 \\ 0 & 0 & m & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \cdot \begin{pmatrix} x_{new1} \\ y_{new1} \\ z_{new1} \\ 1 \end{pmatrix} \quad (10)$$

In Eq. (10), y_{new2} , x_{new2} , and z_{new2} represent the scaled coordinates of the midpoint of the flower model in three dimensions. The rotation change of the flower model involves changes in the rotation axis and rotation angle, with the rotation angle control calculation given by Eq. (11).

$$\eta = \arccos\left(\frac{b}{a}\right) \quad (11)$$

In Eq. (11), η represents the rotation angle of the flower model, a represents the major axis of the flower's generalized shape, and b represents the minor axis. The control Eq. with axis x as the rotation axis is shown in (12).

$$x_L = \frac{x_{C''} - x_{A''}}{a} \quad (12)$$

In Eq. (12), L represents the rotation axis, x_L denotes rotation around the axis x , and A'' , C'' , B'' represent the global coordinates of the flower model. From this, the control Eq. for rotation around the axis y can be deduced, as shown in Eq. (13).

$$y_L = \frac{y_{C''} - y_{A''}}{a} \quad (13)$$

In Eq. (13), y_L represents rotation around the axis y . From Eq. (13), the calculation Eq. for the rotational change of the flower model can be derived, as shown in Eq. (14).

$$\begin{pmatrix} x_{new3} \\ y_{new3} \\ z_{new3} \\ 1 \end{pmatrix} = \begin{bmatrix} \cos\eta + x_L^2(1-\cos\eta) & x_L y_L(1-\cos\eta) & y_L \sin\eta & 0 \\ y_L x_L(1-\cos\eta) & \cos\eta + y_L^2(1-\cos\eta) - x_L \sin\eta & 0 & 0 \\ -y_L \sin\eta & x_L \sin\eta & \cos\eta & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \cdot \begin{pmatrix} x_{new2} \\ y_{new2} \\ z_{new2} \\ 1 \end{pmatrix} \quad (14)$$

In Eq. (14), x_{new3} , y_{new3} , and z_{new3} represent the scaled coordinates of the midpoint of the flower model in three dimensions. In summary, the study employs a 3D data-driven graphics editing algorithm to convert a 3D model into a 2D image, as shown in Fig. 5.

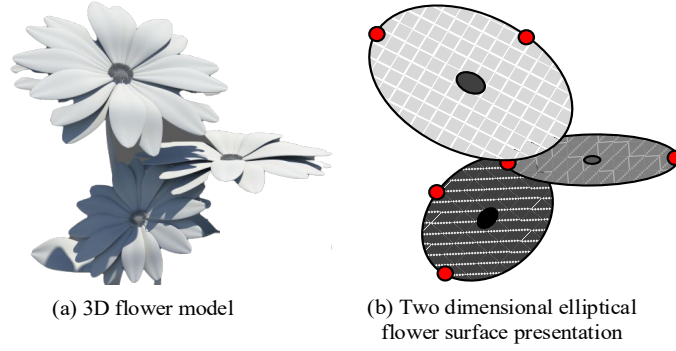


Fig. 5. Schematic diagram of combination generation of translation, rotation, and scaling of flower model

2.3. Weave Pattern Design System Based on 3D Data Graphic Generation Algorithm

After mastering the generation method for weaving patterns, it is necessary to integrate the generated patterns into design weaving. Therefore, a weave design system that generates graphics from 3D model data is proposed. The selected weaving method is weft-knitting technology, which has lower production efficiency. This weaving technology involves placing one or more open hanging arcs on some loops of the knitted fabric, in addition to a closed old loop (Bhosle et al., 2023). Its structural units are loops and hanging arcs. Weft-knitting is generally divided into single-sided and double-sided jacquard, and its pattern styles often exhibit both uniformity and specificity. Since the research aims to generate two-dimensional patterns from three-dimensional models, it is also necessary to perform grayscale processing on the generated patterns to ensure consistent thread usage during weaving. The grayscale processing formula for the image is given by Eq. (15).

$$f(i, j) = 0.2989 \times R(i, j) + 0.5870 \times G(i, j) + 0.1140 \times B(i, j) \quad (15)$$

In Eq. (15), $f(i, j)$ represents the gray value of the flower model, and $R(i, j)$, $G(i, j)$, and $B(i, j)$ represent the red, green, and blue components of the pixel in row i and column j of the generated image. After the fabric pattern is generated, it needs to be imported into the design system connected to the jacquard loom. In addition, one of the core functions of the system built in this study is to quickly convert 2D images into 3D models, which primarily relies on 3D flower model data. The specific conversion steps are as follows. Firstly, the front image of the floral pattern needs to be uploaded, and the edge contours of each petal need to be extracted via interactive operations. Subsequently, a side view of the flower pattern also needs to be uploaded to extract the flower's three-dimensional depth information and curvature data. The extracted information is used to assign depth values to the sampling points along the flower contour, thereby obtaining three-dimensional coordinate data, while the curvature data is used for subsequent mesh deformation. In summary, the research-built fabric pattern design system includes four main aspects: conversion from two-dimensional images to three-dimensional data, two-dimensional pattern creation and generation based on three-dimensional data, production of artistic drawings, and data storage. The research-built fabric pattern design system is shown in Fig. 6.

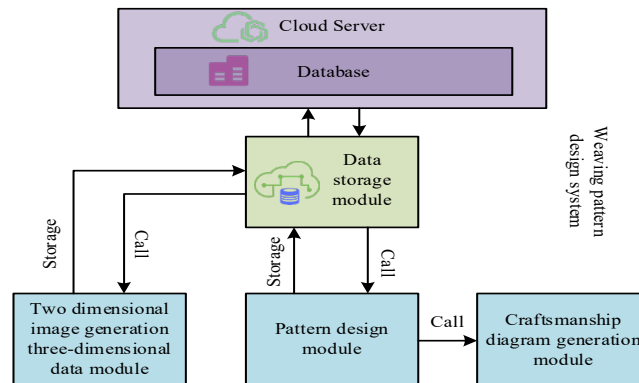


Fig. 6. Weaving pattern design system

As shown in Fig. 6, in addition to the module for converting 2D images into 3D data, there are three modules: creation and generation of 2D patterns based on 3D data, production of design sketches, and data storage. The 2D pattern generation module simplifies the 3D model into a flat elliptical sheet, allowing designers to adjust the design layout by modifying the elliptical sheet. The core task of the design sketch generation module is to transform the flower patterns from the previous step into multicolored jacquard design sketches. As the name suggests, the data storage module stores the data generated at each step for easy retrieval and reuse.

3. Results

3.1. Interactive Model Detection of Fabric Patterns

To verify the effectiveness of the fabric pattern model proposed in the research, which is based on modeling flowers from both the front and side angles, in accurately reproducing flower patterns, an experiment was conducted. The experimental environment is as follows: the processor is an Intel Core i7-9700K, the graphics card is an NVIDIA GeForce RTX 2070, the cooling system is efficient, and the memory is 64GB. The modeling software uses 3ds Max and Blender, the CPU is Intel (R) Core™ i5-9600k, and the system platform is Win 10. Image processing is done in Adobe Photoshop 2020, and the programming environment is PyCharm. The experiment first verified the accuracy of extracting sampling points from the flower contours proposed in the research. The experimental data were obtained from an environmental art design project aimed at enhancing the efficiency and accuracy of floral pattern design using 3D modeling technology. Therefore, the experiment collected a series of flower images of various types and shapes, including simple and complex petal structures, to ensure the broad applicability of the results. The experiment used the Oxford 102 flower dataset, which contains 102 categories and 8189 flower images, covering a variety of petal structures from simple to complex. In the contour extraction experiment, images from each category were randomly split into training and testing sets at a 7:3 ratio. The training set was used to determine the parameter threshold in the contour sampling point extraction algorithm, including the fitting parameters of the central axis curve and the sampling density of the left and right contour lines. The test set is used to evaluate the completeness and accuracy of the algorithm's contour extraction on unseen images. To avoid bias introduced by data partitioning, the partitioning process is repeated 5 times, and the average of each indicator is used as the final result. The main evaluation criteria for the experiment were the completeness and accuracy of sampling point extraction from images using the proposed method. Accuracy is defined as the ratio of pixel level matching between the contour curve extracted by the algorithm and the manually annotated true contour. Integrity is defined as the ratio of the length of the contour extracted by the algorithm to the total length of the true contour. Stability is defined as the degree of variation in evaluation metrics obtained by the same algorithm across multiple runs or across different images, quantified by standard deviation. To ensure the fairness of the experiment, geometric contour extraction and Canny edge detection, which are commonly used for processing complex image edges, were also introduced as comparative methods. The comparison results are shown in Fig. 7.

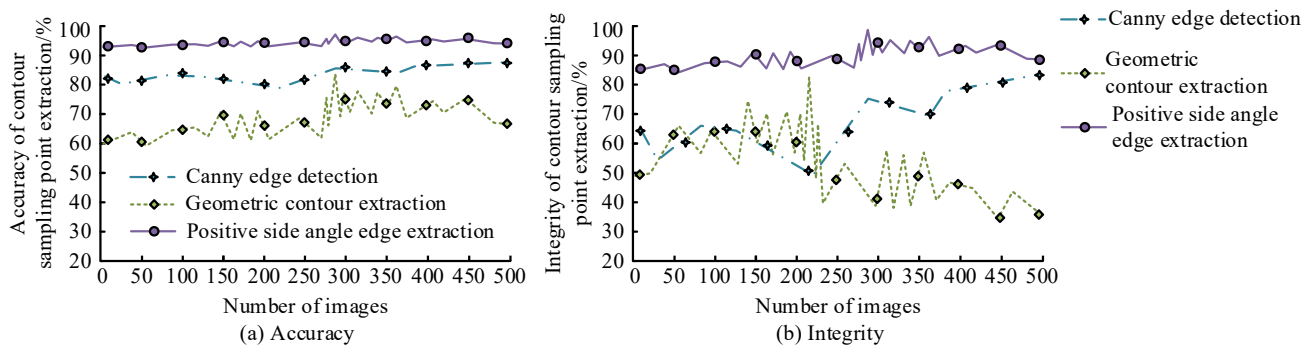


Fig. 7. Comparison of three methods for extracting flower contour curves

In Fig. 7(a), the method proposed in the study, which extracts contour sampling points based on the front and side angles of flowers, maintained over 90% accuracy throughout the experiment. In contrast, the accuracy of Canny edge detection and geometric contour extraction fluctuated significantly, and their average values were lower than those of the front- and side-angle method. The geometric contour extraction method had the lowest detection accuracy, ranging from 60% to 80%. In Fig. 7(b), the method proposed in the study, which extracts contour sampling points based on the front and side angles of flowers, maintained an extraction completeness of over 85% throughout the experiment, reaching 100%. This indicated that the proposed method could capture the contour information of flowers more comprehensively. However, geometric contour extraction exhibited reduced completeness for complex petal structures, resulting in the worst overall performance. The above results demonstrated that the proposed method could more effectively process flower images of different types and morphologies, especially when dealing with complex petal structures, where its superiority was even more evident. It also showed that this method could improve the efficiency of weaving pattern design and more quickly transform natural elements into weaving patterns. The experiment then proceeded to generate 3D models using the contour information extracted by the three methods, comparing the consistency of the 3D models with the 2D images. The results are shown in Fig. 8.

In Fig. 8(b), the model grid generated by the proposed method closely followed the contour of the flower image, including the clear misalignment at the base of the petals. In Fig. 8(c), it was evident that the model grid generated by the geometric contour method had rigid edges, fewer turning angles, and significant differences from the original image. In weaving design, the model image generated by the geometric contour method appeared rough, resulting in a relatively low-quality final presentation. In Fig. 8(d), the model grid generated by the Canny edge detection method had rough edges and a fragmented structure. The above results demonstrated that the proposed method maintained high consistency with the original image, resulting in a smooth, clear, and fluid model presentation. This three-dimensional representation offered advantages in rendering images combined with flowers, greatly improving the efficiency of weaving image generation.

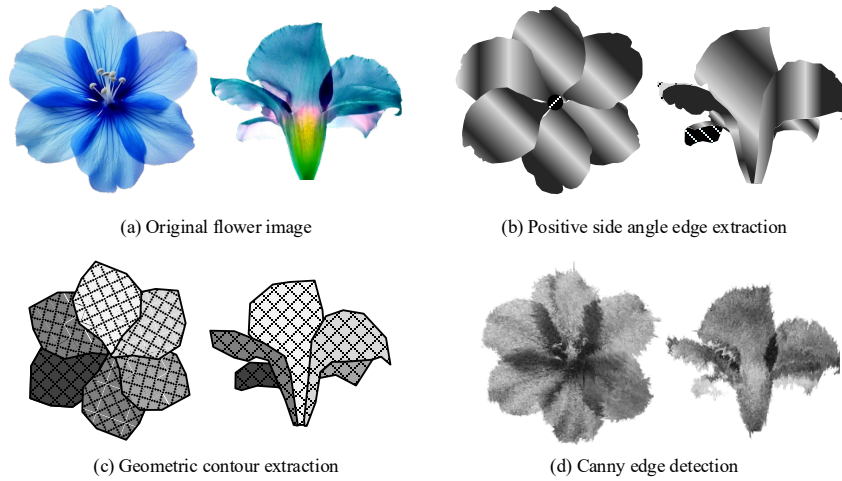


Fig. 8. Consistency between three methods: 3D models and 2D images

3.2. Analysis of 3D Data Graph Generation Algorithm

To verify the advantages of the 3D-based graphic editing algorithm proposed in the study, a series of experiments was conducted. Initially, the model's accuracy after deformation was tested, and a relatively advanced constrained deformation algorithm was introduced for comparison. The deformation accuracy of the model under the two methods is shown in Fig. 9. The experiment involved rotating, translating, scaling, and other operations on the model to verify the advantages of combining the individual components of the OBB bounding box used in the study.

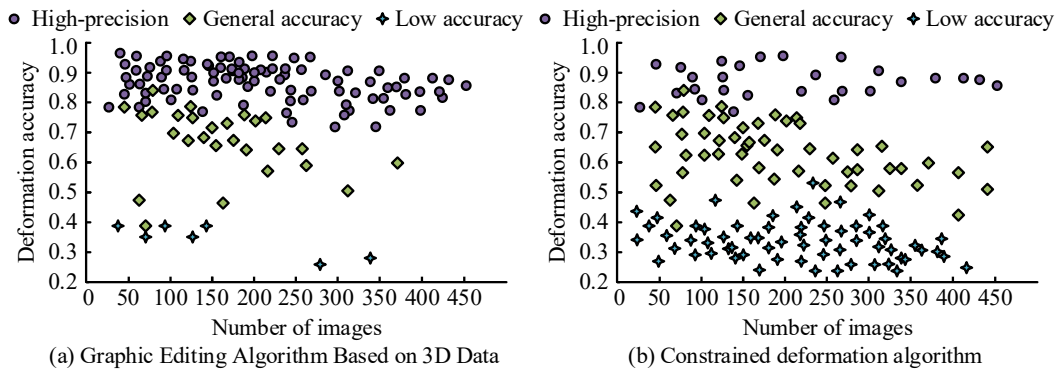


Fig. 9. Model deformation accuracy under two methods

In Fig. 9(a), the graphic editing algorithm proposed in this research, based on 3D data, exhibited high-precision deformation representation across different model volumes. The graphic editing algorithm proposed by the research was less affected by the number of models. When the number of models was less than 250, the high-precision processing state exhibited a dense point distribution with a numerical range of 0.8-1.0. When the number of models exceeded 250, the high-precision distribution points gradually became sparse, with a numerical range of 0.7-0.9. The high-precision processing state is defined as the state in which the average Euclidean distance between each vertex's coordinates and the target coordinates after model deformation is less than 0.01 units. However, the low-precision processing state points were less widely distributed, indicating that the proposed method effectively controlled the models and could assist in designing refined weaving patterns. In Fig. 9(b), the constrained deformation algorithm exhibited different processing states across different model volumes. When the number of models was less than 100, the high-precision processing state had slightly more distribution points with a numerical range of 0.8-0.95. When the number of models exceeded 100, the high-precision distribution points gradually became sparse, with a numerical range of 0.8-0.9. The low-precision processing state points were widely distributed, indicating that the deformation constraint algorithm exerted poor control over the models, and the pattern generation effect was also poor in practical applications. Next, the algorithm's performance was verified through experiments, and a traditional deformation algorithm, linear interpolation, was introduced. The performance comparison of the three algorithms is shown in Fig. 10.

In Fig. 10(a), the calculation speed curve of the proposed method exhibited a steady extension. As the number of models increased, the calculation time remained between 4.8s and 5.0s. In contrast, the calculation speed curves for the other two algorithms showed significant fluctuations, with calculation time decreasing as the number of models increased. Among them, the slowest calculation speed was achieved by the traditional deformation algorithm, namely the linear interpolation algorithm. When the number of models was 100 or more, the calculation time could increase to 20s. This indicated that the proposed method achieved faster processing and calculation speeds in practical applications, facilitating the generation of

large-scale images and improving design efficiency. As shown in Fig. 10(b), the image generation calculation speed and accuracy of the proposed method exhibited a steady upward trend. As the number of models increased, the generation accuracy remained between 95% and 99%. In contrast, the image-generation accuracy curves for the other two algorithms showed significant fluctuations. The lowest generation accuracy was achieved by the linear interpolation algorithm. When the number of models was at least 50, their generation accuracy could drop to 82%. This suggested that the proposed method achieved higher pattern-generation accuracy in practical applications, facilitating the generation of large-scale images and improving design efficiency. The experiment compared the performance of the proposed method against several graphics-editing-related algorithms, and ablation studies were conducted. To evaluate the statistical robustness and performance variability of each algorithm, all experiments were independently repeated five times. The results are shown in Table 1.

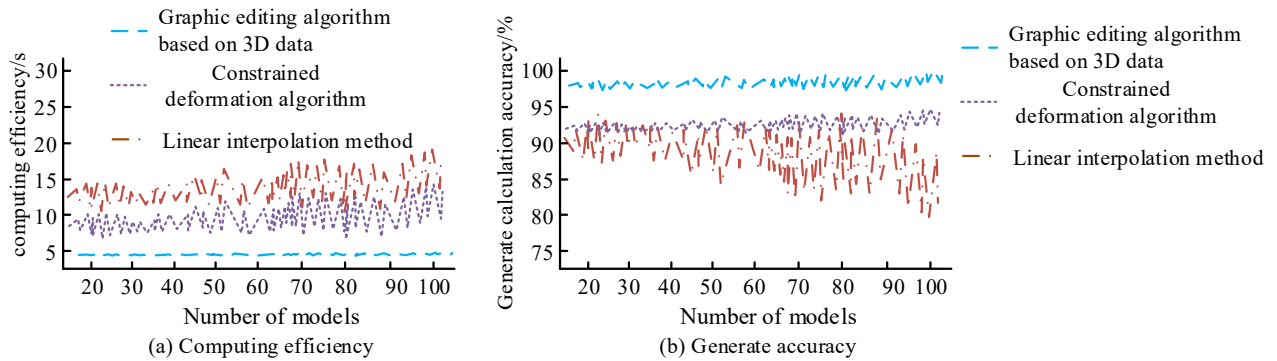


Fig. 10. Performance comparison results of three algorithms

Table 1. Experimental results of ablation for all algorithm models

Model	MSE	RMSE	MAE
Graphic editing algorithm based on 3D data	0.41 ± 0.05	0.002 ± 0.0004	0.0022 ± 0.0004
Graphic editing algorithm based on 3D data-OBB	0.25 ± 0.03	0.001 ± 0.0002	0.0017 ± 0.0003
Linear interpolation algorithm	0.50 ± 0.07	0.007 ± 0.0012	0.0044 ± 0.0006
Constrained deformation algorithm	0.46 ± 0.06	0.011 ± 0.0018	0.0010 ± 0.0002

As shown in Table 1, a paired t-test indicated that the algorithm proposed in the research, which incorporates OBB, showed statistically significant differences in Mean Squared Error (MSE) compared to the version without OBB ($p < 0.05$). Compared with the linear interpolation and constrained deformation algorithms, the three error indicators were significantly lower ($p < 0.01$). These results indicate that the graphic editing algorithm incorporating OBB outperforms all the comparison methods in terms of error control and statistical robustness. These comparative data validated the superiority of the proposed graphic editing algorithm, which combines 3D data with OBB bounding boxes, in the fields of model transformation control and image generation, thereby effectively improving weaving efficiency and design precision.

3.3. Simulation Analysis of Fabric Pattern Design System

At the end of the experiment, the proposed fabric pattern design system was validated. In modern industrial production, the stability of the fabric pattern design system is crucial for maintaining production efficiency and quality. System stability directly affects the continuity of the production process and the consistency of the products. Therefore, evaluating the stability of the fabric pattern design system is crucial to ensuring its reliability and effectiveness in real-world production environments. The experiment verified the system's performance and advantages by recording its stability during different operational periods and comparing it with traditional hand-drawn designs. The results are shown in Fig. 11.

As evident in Fig. 11, the efficiency disparity between the research-designed fabric pattern design system and the traditional hand-drawn design was clear. The stability of the fabric pattern design system generally surpassed that of traditional hand-drawn design. The stability of the design system remained mostly above 94%, whereas the stability of traditional hand-drawn design fluctuated between 91% and 94%, and its efficiency tended to decrease over time. This indicated that the design system maintained high stability during prolonged operation, whereas traditional hand-drawn design exhibited significant fluctuations. The fabric pattern design system demonstrated greater stability during prolonged operation, which was crucial for continuity and consistency in industrial production. Compared to traditional hand-drawn design, the design system may have reduced the impact of human error and subjective judgments, thereby enhancing production efficiency and product quality. Improving system stability in practical applications could have reduced costs incurred due to

production interruptions and quality control issues. At the end of the experiment, the generation effect of the fabric pattern design system was verified, and the results are shown in Fig. 12.

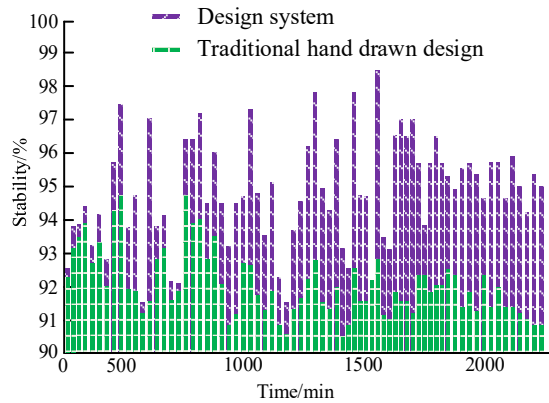


Fig. 11. Comparison between weaving pattern design system and traditional hand drawn design

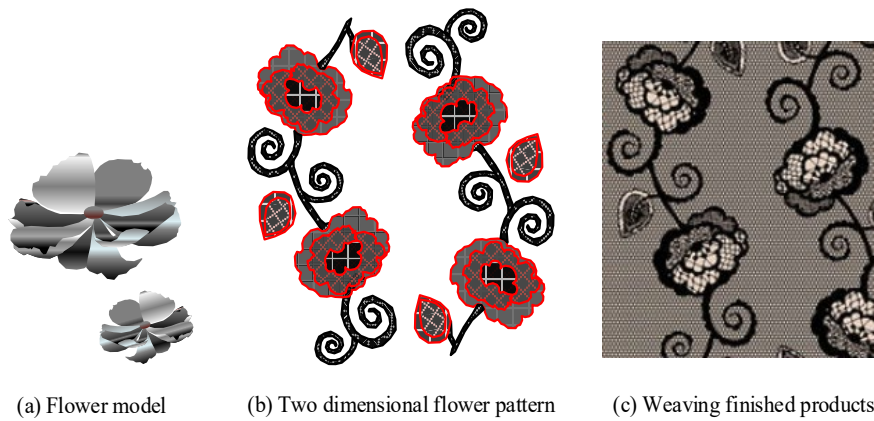


Fig. 12. Schematic diagram of pattern generation effect of woven fabric pattern design system

In Fig. 12, the system combined, deformed, rotated, and scaled the three-dimensional model of flowers in Fig. 12(a) to generate different styles, thereby batch-generating two-dimensional images. The two-dimensional pattern creation and generation module, based on three-dimensional data, simplified the planar projection of the three-dimensional model into a two-dimensional ellipse. Designers could lay out and adjust the three-dimensional model by drawing this simple two-dimensional elliptical shape. Subsequently, an artistic design diagram like Fig. 12(b) was generated, in which the floral pattern from the previous step was transformed into a jacquard artistic design diagram with multiple colors. The generated image was stored through the data storage module for easy retrieval and reuse during subsequent design. Finally, the woven pattern in Fig. 12(c) was obtained through a weaving machine. The proposed woven pattern design system clearly presented woven patterns, and its intelligent generation and storage greatly improved design efficiency, demonstrating the system's efficiency and intelligent advantages.

4. Conclusion

Flowers are a common type in modern textile pattern design. However, due to the wide variety and complex, variable structures of flowers, it is difficult to achieve computer-aided design, such as three-dimensional modeling. Therefore, quickly completing the 3D reconstruction of flowers and applying the design of textile patterns have become urgent technical challenges. Based on this, the study proposes a method that combines a 3D data-driven graphic editing algorithm with an OBB bounding box to build a textile pattern design system. The results showed that the proposed method's calculation speed curve exhibited a stable upward trend. As the number of models increased, the calculation time remained between 4.8s and 5.0s. This indicated that the proposed method had faster processing and calculation speed in practical applications, facilitating the generation of large-scale images and improving design efficiency. The accuracy of image generation calculation of the proposed method showed a steady upward trend. As the number of models increased, the generation accuracy remained between 95% and 99%. The efficiency difference between the textile pattern design system designed in the study and the traditional hand-drawn design was that the stability of the textile pattern design system was generally higher than that of the traditional hand-drawn design. The design system's stability was consistently maintained above 94%. The research results showed that the proposed method could quickly complete the three-dimensional reconstruction of complex flowers. When the research method was applied in practice, rapid three-dimensional reconstruction and high-precision image

generation accelerated the design and production process of textile patterns. Based on the findings of this study, textile production managers can replace the traditional manual floral pattern-drawing process with an automated 3D reconstruction and 2D sketch-generation system to reduce manual drawing time. The system's rapid generation capabilities can be used to restructure the design verification process, shortening the prototyping cycle from concept sketches to production preparation. Simultaneously, standardized data generation and storage modules replace manual drawing based on personal experience, improving the consistency of jacquard design preparation and reducing rework and waste caused by design misunderstandings. However, there are still limitations to the research, as the dataset is relatively small and there is a risk of overfitting. Meanwhile, the proposed system has not been validated in actual weaving production environments, and its stability and adaptability in industrial scenarios still need to be tested. Future research can use multi-source datasets to enhance reliability and conduct small-scale industrial pilot tests to evaluate the system's performance under real production conditions.

Author Contributions

Junling Li contributed to conceptualization, methodology, software, data collection, draft preparation, project administration and funding acquisition. Fujun Wang contributed to methodology, manuscript editing, visualization, supervision, project administration, and funding acquisition. All authors have read and agreed with the manuscript before its submission and publication.

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Institutional Review Board Statement

Not applicable.

Declaration of Artificial Intelligence (AI) Tools

The authors confirm that no AI tools were used in the preparation of this manuscript.

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