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Evaluation and analysis of AI-supported sustainable fashion design

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Abstract Digital design offers sustainable fashion design the possibility of continuous development. This paper proposes an intelligent clothing generation framework that integrates the improved iterative closest point (ICP) algorithm with a particle-spring physical model to achieve precise virtual generation of fashion clothing. The ICP algorithm is used to preprocess human point cloud data, removing incorrect corresponding point pairs, and combining four types of constraints to improve the accuracy of coordinate transformation. A particle-spring model is constructed using fabric dynamics simulation to simulate the effects of particle forces, enhancing the realism of clothing design. Experimental results show that the average error in generating clothing components is below 1.5%. The time required for model adjustment operations for three different types of clothing is only 9, 8, and 10 seconds, respectively, with post-adjustment errors below 0.70%. The trajectory error of the generated clothing model is less than 0.30, with maximum average curvature and average position errors of 19.6% and 2.649 units, respectively.

Index Terms ICP algorithm, particle-spring model, point cloud processing, coordinate constraints, sustainable fashion

I. Introduction

Artificial intelligence (AI) technology, as the core driving force behind technological development in the 21st century, is transforming every aspect of human society with its unique charm and far-reaching influence. This technology stems from in-depth exploration and simulation of human intelligence, leveraging cutting-edge techniques such as machine learning, deep learning, natural language processing, and computer vision to endow machines with the ability to perceive, understand, make decisions, and even create [1], [2]. In the world of artificial intelligence, algorithms are the soul, and data is the nourishment, together weaving the future landscape of intelligence [3]. The rise of artificial intelligence technology has not only driven the rapid development of the technology industry but has also brought unprecedented transformation to the field of artistic creation [4], [5]. In the field of fashion design, where tradition and innovation coexist, the integration of artificial intelligence technology has undoubtedly provided designers with new creative tools and ways of thinking [6].

With the assistance of AI technology, fashion design is no longer constrained by traditional materials and processes but instead presents unlimited creativity and possibilities in a digital form [7]. For example, Reference [8] proposes a novel AI-based fashion design framework that employs generative adversarial network (GAN) technology, including sketch generation and rendering generation modules, aiming to enhance designers' efficiency by balancing controllability and randomness during the design process. Reference [9] proposes a method for interactive fashion image processing using AI-generated models, determining appropriate styles through user-centered design. Literature [10] develops an AI-based fashion apparel development system that integrates fashion industry knowledge and reflects human designers' workflows. Literature [11] explores consumers' reactions to AI-designed fashion products, finding that consumers prefer human-designed products due to concerns about authenticity and quality. However, AI-provided personalized options can mitigate negative reactions to AI-designed products to some extent. Literature [12] explores the application of AI in fashion design, finding that it can enhance personalization and multi-modal interaction experiences, enabling designers and consumers to co-create unique design works and drive innovation in the fashion industry. Literature [13] explores the innovative application of AI and machine learning technologies in ethnic fashion design, emphasizing the combination of AI with multi-dimensional human body modeling technology to achieve body-type customized fabric selection and innovative design, thereby driving the future development of the fashion industry. Literature [14] introduces CrossGAI, a collaborative fashion design system that leverages AI-enhanced sketch assistance and can be deployed on a local area network, thereby improving efficiency and quality while ensuring privacy and security.

In today's society, people are paying unprecedented attention to environmental protection. Industries are increasingly recognizing the necessity of monitoring the environmental impact of their operations, and the fashion industry is no exception. The concept of “sustainable fashion” has sparked global discussion, with industry brands gradually recognizing the importance of balancing environmental protection and social responsibility while pursuing economic benefits [15]-[17]. With the rise of social media and diversified communication channels, discussions about sustainable fashion have grown increasingly intense. This concept requires the entire fashion industry to achieve sustainable development and establish a transparent supply chain system [18], [19]. Specifically, fashion products should prioritize durability and recyclability (given that these two characteristics are not always compatible, innovative design must be employed to achieve the optimal balance). From an ecological perspective, the core lies in minimizing the negative environmental impact of operations. Given the finite nature of Earth's resources, it is essential to achieve minimal and optimal resource utilization [20]-[23]. From a social perspective, it is necessary to ensure that all stakeholders across the supply chain enjoy reasonable working conditions and to promote broader societal benefits from sustainable fashion.

This paper simplifies the clothing design process by compressing traditional multi-stage manual operations into three steps of digital processing, thereby improving the convenience of fashion clothing design. An improved ICP algorithm with curvature constraints is adopted to solve point cloud data misalignment issues, and precise position registration is achieved through distance threshold comparison and SVD matrix decomposition. A particle-spring fabric model is established, incorporating three-mode springs for stretching, shearing, and bending, along with aerodynamic equations, to accurately simulate the movement characteristics of fabric under force fields, thereby enhancing the reliability of intelligent design. Through error calculations and comparative experiments, the effectiveness of the proposed method in generating clothing designs is validated.

II. Analysis of the technical implementation process of fashion virtual design

II. A. Simplifying the clothing design process

In the process of creating virtual clothing, specialized knowledge of clothing pattern making is required, and the designs must be rendered using 3D modeling software. This means that virtual clothing designers must possess both a comprehensive understanding of clothing design and production, as well as the ability to operate digital modeling software. Figure 1 illustrates the virtual clothing production process. For ordinary fashion enthusiasts or digital platform users, this process requires significant time and learning costs, which can significantly dampen user enthusiasm. Therefore, in the process design of the virtual clothing co-creation platform, this paper places particular emphasis on user participation in the design process, aiming for a simple, convenient, and low-cost co-creation experience.

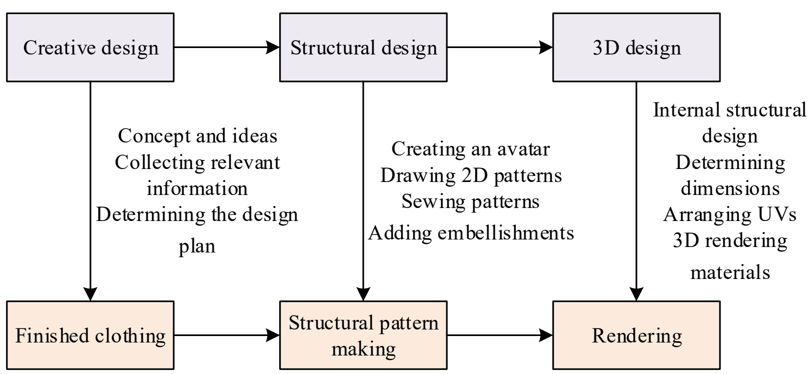

Figure 1: The virtual clothing production process

To ensure that users are easy to use, happy and satisfied, this is achieved by designing an intuitive user interface, providing a clear design flow, and providing good user support. In terms of platform interface display, the standard of the interface should be easy to use, intuitive, and beautiful, so that users can quickly locate the entrance of each function, and provide relevant feedback in a timely manner after interaction, so as to avoid unresponsive operations. When it comes to the design process, platforms need to consider the extent to which users are involved in the design and their role in the design process, which helps ensure that users are able to play their part in the platform design process and get more value out of it. For ordinary users, the platform needs to disassemble the process of virtual clothing design, simplify it, and use a clear display and interaction method to enable users to quickly complete the co-creation process and achieve the goal. Figure 2 shows a simplified version of the virtual costume production process. In the co-creation process, design can be done in a modular way, where the garment is precisely disassembled into separate parts, each of which can be deconstructed and reassembled along with the others.

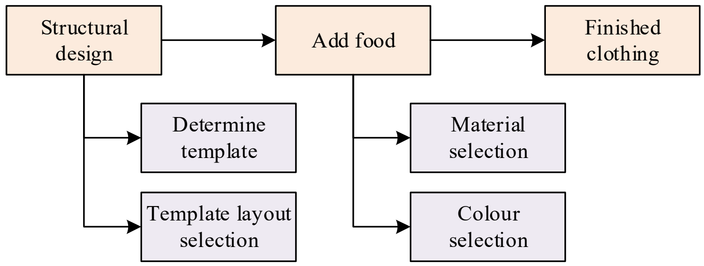

Figure 2: The simplified production process of virtual clothing

During the design process, each user has their own preferences and tastes. Therefore, it is important to consider users' personalized needs and provide them with more diverse and targeted customization tools and functions that allow them to express their creativity and style. As such, a virtual clothing co-creation platform requires a pre-made template library and a wide range of color and texture options. As the platform develops, more professional design tools, such as 3D modeling and virtual try-on, will need to be introduced for more advanced and professional users.

II. B. Overview of ICP splicing principles

The two point clouds to be merged are first constrained according to certain criteria to establish corresponding point sets P and Q, where the number of corresponding data point pairs is n. Then, the optimal coordinate transformation, i.e., the rotation matrix R and translation vector T, is calculated iteratively using the moving least squares method so that the error function $E(R,T)=\frac{1}{n}\sum_{k=1}^{n}\left\|q_k-(Rp_k+T)\right\|^2$ is minimized. This paper analyzes the ICP algorithm in three stages: 1) determining the initial corresponding point set; 2) removing incorrect corresponding point pairs; 3) solving the coordinate transformation.

II. B. 1) Determining the initial set of corresponding points

For the two surfaces $Q_1(u,v)$ and $Q_2(u,v)$ of the fitting function $f(x)$, use the following method to establish the initial corresponding point set. Select k points $\{p_1,p_2,\cdots,p_k\}$ uniformly on the surface $Q_1(u,v)$, and perform the following operations on each point p_i:

1) First, calculate the normal vector $n_i=\frac{S_U\times S_V}{\left\|S_U\times S_V\right\|}$ of the surface $Q_1(u,v)$ at p_i. The line passing through point p_i with direction vector n_i can be represented as $L_i=\{a\,|\,(p_i-a)\times n_i=0.0\}$. Then, the intersection point q_i between the line and the surface $Q_2(u,v)$ is calculated.

2) Within the neighborhood of point q_i (the r-neighborhood of point q_i is defined as a spherical neighborhood with center at point q_i and radius r), arbitrarily select a point q_i', and use the method from the first step to construct its normal vector. and intersect the surface $Q_1(u,v)$ in the opposite direction of the normal to obtain the intersection point p_i'. Thus, two pairs of initial corresponding points (p_i,q_i) and (p_i',q_i').

3) Return to Step 1 and repeat the above steps until all k points have been processed. Ultimately, $4k$ pairs of initial corresponding points can be established.

II. B. 2) Removing incorrect corresponding points

The initial set of corresponding points can be established by intersecting the normal with the surface twice, and two pairs of corresponding points (p_i,q_i) and (p_i',q_i') can be found at once, where point q_i' is a point within an r neighborhood of point q_i on surface $Q_2(u,v)$. For the candidate corresponding point pairs (p_i,q_i) and (p_i',q_i') established using the traditional point-to-point ICP algorithm, the following applies:

1) Directional constraint: $(p_i'-p_i)\cdot(q_i'-q_i)\geq 0.0$;

2) Rigidity constraint: $\|q_i' - q_i\| \le 2\left(e_1 + \|p_i' - p_i\|\right)$;

3) Matching error constraint: $\|q_i' - q_i\| \le e_1 + \|p_i' - p_i\|$;

Let $e_1 = \|p_i - q_i\|$. Among these, the directionality constraint can remove half of the incorrect point pairs, the rigidity constraint can only remove a small number, while the matching error constraint typically removes a larger number of incorrect point pairs. The above three constraints can eliminate most of the incorrect corresponding point pairs, but since they do not consider the correctness of a pair of corresponding points themselves, some incorrect corresponding point pairs still exist and are not completely eliminated. To address this issue, the paper also introduces a curvature constraint. Curvature can accurately describe the local geometric characteristics of a point on a surface, and the curvature values between correct corresponding points should be the same or basically the same.

For the point pair (p_i, q_i), the similarity measure can be used: $\|k_1(p_i) - k_1(q_i)\| + \|k_2(p_i) - k_2(q_i)\| \le \hat{o}$, where $\hat{o}$ is a given threshold, typically ranging from 15% to 20%. In this paper, the iteration takes the threshold $\hat{o} = 15\%$, and k_1 and k_2 are the principal curvatures.

For the surface $Q(u,v)$, the calculation method is as follows:

First, calculate the two basic quantities of the surface: $E = S_u S_u$, $F = S_u S_v$, $G = S_v S_v$, $M = nS_{uv}$, $L = nS_{uu}$ and $N = nS_{vv}$; where $n = \dfrac{S_u \times S_v}{\|S_u \times S_v\|}$ is the unit normal vector.

The Gaussian curvature is: $K = \dfrac{LN - M^2}{2\left(EG - F^2\right)}$; the mean curvature is: $H = \dfrac{EN - 2FM + GL}{2\left(EG - F^2\right)}$.

The principal curvatures can be obtained from the Gaussian curvature and mean curvature: $k_1 = H - \sqrt{H^2 - K}$ and $k_2 = H + \sqrt{H^2 - K}$.

Directional constraints, rigidity constraints, and matching error constraints utilize the consistency of rigid motion between adjacent candidate corresponding point pairs to represent the constraint relationships between points on the surface, while curvature constraints utilize the geometric invariance of points on the surface to represent the constraint relationships of individual points. This paper organically combines these four constraints to effectively eliminate incorrect corresponding point pairs and significantly improve the accuracy of solving the optimal coordinate transformation matrix.

II. B. 3) Solving coordinate changes

The algorithm determines the final corresponding point set by solving for the optimal coordinate transformation between the two point clouds using the moving least squares iterative method. For computational efficiency, singular value decomposition (SVD) is used.

1) Calculate the centroids of point sets Q and P respectively: $\bar{u}_q = \frac{1}{n}\sum_{i=1}^{n} Q_i$ and $\bar{u}_p = \frac{1}{n}\sum_{i=1}^{n} P_i$;

2) Let the matrix $H_{3\times3} = \frac{1}{n}\sum_{i=1}^{n}\left(P_i - \bar{u}_p\right)\left(Q_i - \bar{u}_q\right)^T$;

3) Perform singular value decomposition on matrix H to obtain: $H = U\Sigma V^T$;

where matrix $\Sigma = diag(d_i)$ and $d_1 \ge d_2 \ge d_3 \ge 0$;

4) Let $A = \begin{cases} I_3 & \det(U)\det(V) \ge 0 \\ diag(1,1,-1) & \det(U)\det(V) < 0 \end{cases}$ If the matrix $rank(H) \ge 2.0$, then the rotation matrix can be obtained:

$$R = UAV^T \tag{1}$$

5) Based on the rotation matrix R and the centers of gravity $\bar{u}_q$ and $\bar{u}_p$ of the two point sets, the following can be calculated:

$$\text{Translation vector}: \ t = \bar{u}_q - R\bar{u}_p \tag{2}$$

Typically, a single transformation is insufficient to achieve the required accuracy, so multiple iterations are necessary to find the optimal transformation matrix, with the corresponding point sets recalculated at each iteration. The iteration process ends when the difference between the target equations of two consecutive iterations is less than a specified threshold, or when the threshold of the target equation no longer decreases.

II. C.Physical model of clothing fabrics

II. C. 1) Point-mass-spring model

With the improvement of computer performance, the use of computers for fashion clothing design simulation has become more advantageous and further meets people's high requirements for simulation effects. In practical applications, physics-based fabric modeling methods have gradually become dominant. Among these, the particle-spring model simulation method is computationally simple, offers real-time performance, is easy to implement, and can be used to simulate the complex physical deformation of fabrics. Therefore, this paper primarily employs the particle-spring model simulation method from physics-based modeling to simulate the motion and deformation effects of three-dimensional fabrics.

The particle-spring model establishes a fabric deformation simulation model based on a regular quadrilateral grid, treating the fabric as a virtual rectangular grid structure of size $n \times m$. The intersection points of the grid's warp and weft lines are represented by particles, and each particle is connected to its adjacent particles via springs. Figure 3 illustrates the structure of the particle-spring model. According to Hooke's law: within the elastic limit, the force exerted by a spring is directly proportional to the length by which the spring is stretched or compressed. Therefore, during fabric movement, the interconnected particles cause the springs to continuously stretch and contract, and the forces generated by the springs influence the motion state of the particles. From a holistic perspective, the motion state of all particles collectively represents the overall three-dimensional fabric deformation state.

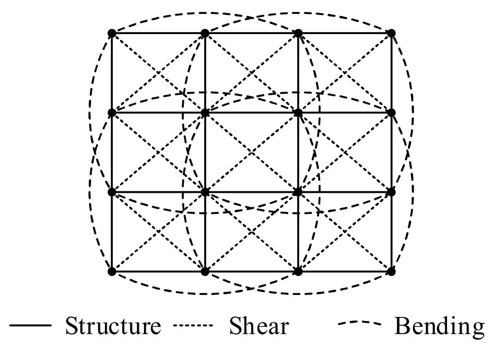

Figure 3: Structure of the particle-spring model

The interaction between particles is achieved through a series of massless springs. To simulate the force-induced deformation and motion of fabric under three conditions—tension and compression, in-plane direction, and out-of-plane direction—structural springs, shear springs, and bending springs are respectively set up in the particle-spring model to connect different particles, thereby representing the mechanical properties of fabric under the three force conditions. Figure 4 shows the structure of the three types of springs.

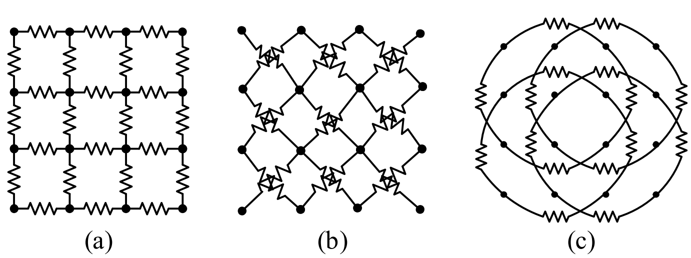

Figure 4: Structures of three kinds of springs

Structural springs simulate the forces acting on the fabric in both the tensile and compressive directions to maintain the intrinsic shape of the particles, preventing excessive deformation of the fabric in both the warp and weft directions. In Figure 4 (a), except for the boundary particles, each particle is connected to its adjacent particles in the warp and weft directions by 4.0 structural springs, making it the spring structure with the highest number of springs.

Shear springs simulate the forces acting in the inclined direction within the fabric to prevent excessive deformation in the diagonal direction during stretching and compression, maintaining a balanced transition of the fabric. In Figure 4 (b), except for the boundary particles, each particle has 4.0 shear springs connected to two particles in the diagonal direction.

Bending springs simulate the forces between two points separated in the longitudinal and transverse directions to prevent excessive unnatural bending of the fabric. In Figure 4 (c), except for the boundary points, each point has 4.0 bending springs connected to two points separated in the longitudinal and transverse directions. The elasticity coefficient of bending springs is generally small and can sometimes be ignored in simulations.

II. C. 2) Stress analysis of clothing fabrics

The previous section provided a brief introduction to the connection method of particles in the particle-spring model. However, the essence of fabric simulation lies in determining the position and velocity of each frame during the fabric's motion. The motion state of each particle depends on the sum of internal and external forces acting on it. Internal forces primarily consist of elastic forces resulting from interactions between particles, namely structural forces, shear forces, and bending forces. External forces primarily include real-world forces such as gravity, air damping force, wind force, and penalty force, as well as forces defined by the system designer. Under the influence of these forces, each particle exhibits the motion trajectory of the small unit it represents. By combining the motion of all particles, the deformation state of the fabric's overall motion can be simulated.

In fabric simulation, the initial state of the fabric is stationary. To simulate the dynamic effects of the fabric over time, its motion can be determined by Newton's Second Law. Newton's Second Law states that at any given moment, when multiple forces act on an object simultaneously, the vector sum of all forces is the total force acting on the object. For each particle, the sum of the internal and external forces acting on it determines the particle's velocity and direction of motion over a time step Δt. By integrating these motion states over time, the motion state of the fabric over a period of time can be simulated. The motion equation for any particle on the fabric at time t is expressed as:

$$m\frac{\partial^2 X}{\partial t^2}=F_{ext}(X,t)+F_{int}(X,t) \tag{3}$$

In the equation, X denotes the position vector of the particle at time t, where $X\in R^3$; m denotes the mass of the particle; $F_{ext}(X,t)$ and $F_{int}(X,t)$ denote the external and internal forces acting on the particle at time t, respectively. These forces are functions of the position X and time t, and they vary with changes in the particle's position and time. At each time step, force analysis must be performed on all particles, and the particles must then move under their new velocities.

In the particle-spring model, particles are connected to structural springs, shear springs, bending springs, and their adjacent particles. Therefore, the internal forces acting on the particles are primarily manifested as elastic forces between springs, including structural forces, shear forces, and bending forces between particles. The internal forces acting on each particle can be expressed as:

$$F_{int}(X,t)=F_{structure}+F_{shearing}+F_{bending} \tag{4}$$

In order to simulate the movement patterns of particles in fabric, it is often necessary to consider not only external forces that exist in nature, such as gravity, air damping force, and penalty force, but also user-defined external forces in the system. The external force acting on each particle can be expressed as:

$$F_{ext}(X,t)=F_{gravity}+F_{damping}+F_{penalty}+F_{user} \tag{5}$$

1) Gravity (G)

In this paper, a regular grid is used to describe the fabric model, assuming that the connection mass between particles is zero and all mass is added to the particles. Each particle has the same mass, which is equal to the total mass of the fabric divided by the number of particles. The gravity acting on each particle can be expressed as:

$$F_{gravity}=mg \tag{6}$$

In the equation, m represents the mass of any point on the fabric, and g represents the gravitational acceleration.

2) Damping force (DF)

During the motion of a point, excessive force may cause excessive oscillation, so a damping force is introduced to maintain the stability of the system. When the damping force is smaller, the particle moves faster but is more prone to unrealistic excessive deformation; when the damping force is larger, the particle moves slower but is more likely to reach a balanced state. In practical applications, the damping coefficient should be selected appropriately based on the requirements of the simulation results. The damping force acting on each particle due to the elastic interaction between particles can be expressed as:

$$F_{damping}=-c_d\frac{\partial X}{\partial t} \tag{7}$$

In the equation, c_d is the damping coefficient.

3) Penalty force (PF)

The penalty force, also known as the anti-collision force, is applied when the fabric model interacts with external objects during motion, and when different parts of the fabric collide with each other. If the motion of the fabric model's particles is not constrained, penetration may occur during collisions. The penalty force can be used to prevent penetration. When a collision is detected between a particle and an external object or another particle, a penalty force $F_{penalty}$ is applied to pull the particle back to the other side of the collision body. For particle p and collision point p_0, the penalty force can be expressed as:

$$\begin{cases} F_{penalty} = C_p \exp\left(\left\|\overline{pp_0}\right\|^{-1}\right) N_{p_0} & \text{Collision occurred} \\ F_{penalty} = 0 & \text{No collision occurred} \end{cases} \tag{8}$$

In the equation, C_p represents the collision coefficient; the larger the coefficient, the greater the recoil force. N_{p_0} represents the unit normal vector at p_0. $\left\|\overline{pp_0}\right\|$ represents the distance component between particle p and collision point p_0 along the direction of N_{p_0}.

4) User-defined force (UDF)

During simulation, to enable user interaction, forces can be manually defined for particles, such as mouse drag force, etc.

III. Application and comparison of intelligent models in fashion apparel generation

III. A. Analysis of clothing effects generated by the model

III. A. 1) Calculation of critical interface errors for each part

Using the intelligent clothing generation model described in this paper, 250 digital fashion garments suitable for different body types were generated, and the generated garments were then subjected to error testing. Figure 5 shows the error statistics for the key cross-sections of the hand clothing. Figure 6 shows the error statistics for the key cross-sections of the torso clothing. Figure 7 shows the error statistics for the key cross-sections of the leg clothing. In the 4 key cross-sections of the hand clothing, the 9 key cross-sections of the torso clothing, and the 6 key cross-sections of the leg clothing, the average error of the clothing generated by the intelligent model is less than 1.5%. The largest average error was observed at the shoulder peak cross-section of the hand, reaching 1.448%. Overall, the average errors for all body parts of the generated clothing are very small, indicating that preprocessing point cloud data using the ICP algorithm can enhance the accuracy of clothing position generation.

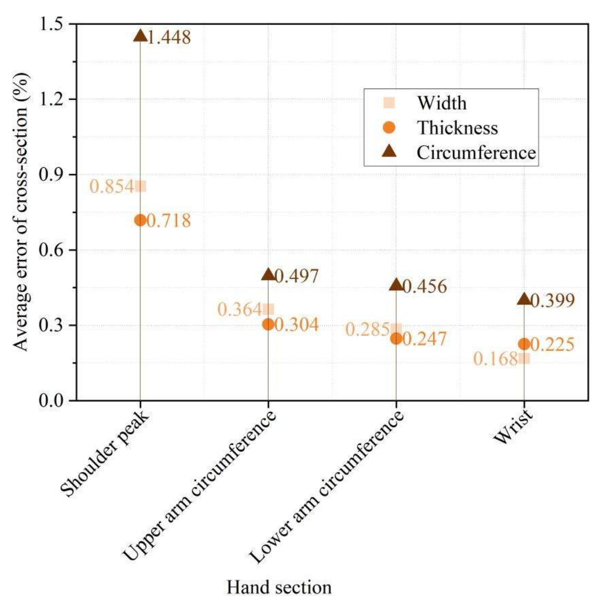

Figure 5: Error of key cross-sections of hand clothing

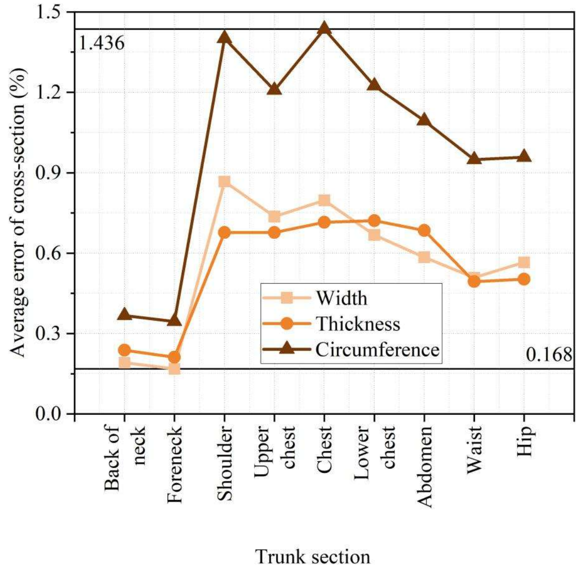

Figure 6: Error of key cross-sections of trunk clothing

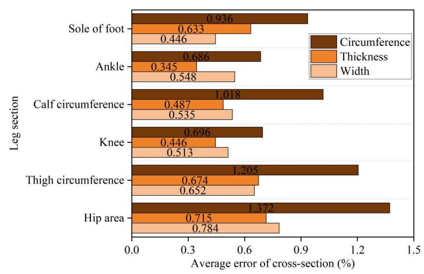

Figure 7: Error of key cross-sections of leg clothing

III. A. 2) Comparison of clothing errors generated before and after point cloud data processing

To further validate the effectiveness of the ICP algorithm in processing point cloud data, a comparative experiment was conducted to test the error rates of the generated garments before and after data processing. Figure 8 shows the overall error comparison results (calculated as the average of the errors in width, thickness, circumference, and volume for each garment). When point cloud data was not preprocessed using ICP, the average error rate for the generated garments ranged from a minimum of 1.178% to a maximum of 2.896%, with overall error fluctuations reaching 1.718%. However, after preprocessing the point cloud data using the ICP algorithm, the average error rate for the generated garments never exceeded 1.250%, and the overall fluctuations were more stable. This further validates that using the ICP algorithm for point cloud data preprocessing can enhance the accuracy of the model's subsequent garment generation and boost users' confidence in participating in fashion design.

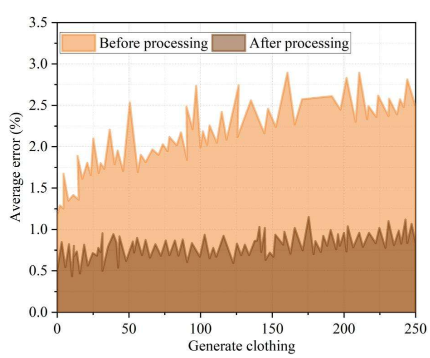

Figure 8: Comparison of clothing errors before and after data processing

III. A. 3) Comparison of the effects of intelligent adjustment and manual adjustment methods

To evaluate the effectiveness of the model-based intelligent adjustment of clothing designs, five users were invited to participate in a clothing design experiment, designing three types of garments (vests, long skirts, and overalls). The study compared the time required for users to manually adjust clothing errors versus the time required for the model to intelligently adjust clothing errors, as well as the clothing errors before and after adjustment using the two methods. Table 1 presents the statistical comparison results between the intelligent adjustment and manual adjustment methods. Using the model for intelligent adjustment of clothing design, the time required for the three types of clothing was 9, 8, and 10 seconds, respectively, compared to 65, 59, and 67 seconds for manual adjustment, resulting in a significant reduction in operation time, enabling users to quickly and seamlessly proceed with their fashion clothing design. Additionally, the average clothing error before and after intelligent adjustment was smaller than that of manual adjustment, with the average error after adjustment not exceeding 0.70%, and the lowest being only 0.59%. By constructing a physical model of clothing fabric using point cloud data processed with the ICP algorithm, the accuracy of users' fashion clothing designs can be significantly improved while accelerating the design process.

Table 1: Statistical comparison results of the two adjustment methods

Clothing type	Operation method	Average error (%)		Operation time (s)
		Before adjustment	After adjustment	
Vest	Manual adjustment	2.73	2.45	65
	Intelligent adjustment	1.01	0.66	9
Long dress	Manual adjustment	2.68	2.30	59
	Intelligent adjustment	1.00	0.59	8
Overalls	Manual adjustment	2.59	2.31	67
	Intelligent adjustment	0.93	0.62	10

III. B. Comparison of clothing performance generated by models

III. B. 1) Comparison of clothing generation trajectories for different models

After verifying the clothing generation performance of the model in this paper, to further study the application advantages of this model, two similar fashion clothing intelligent design models (Neuro Physics and GAFNN) were selected as comparison models to analyze the clothing generation performance of different models. Figure 9 shows the fashion clothing intelligent generation trajectories of the three models. The error values between the fashion clothing generation trajectories of the model in this paper and the actual trajectories are always less than 0.30, with the lowest being only 0.10. In contrast, the deviation of the Neuro Physics model is significant, with a maximum value of 0.87; the deviation of the GAFNN model is smaller compared to Neuro Physics, but it still exhibits a certain degree of deviation from the actual values. Overall, the clothing generation trajectory of the model proposed in this paper aligns most closely with the actual clothing generation trajectory, and the generated fashion clothing is more body-hugging.

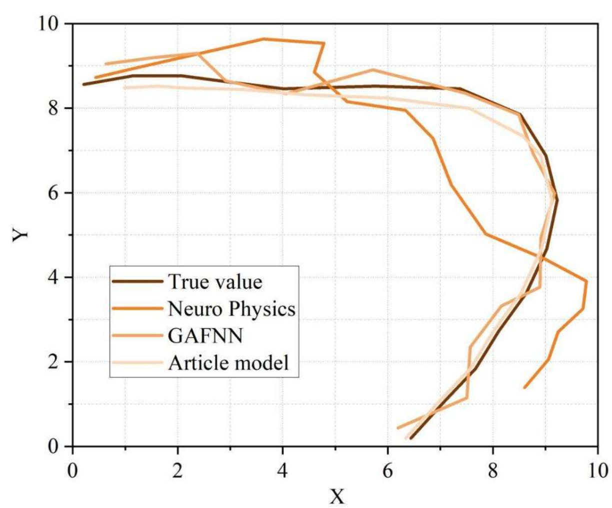

Figure 9: Intelligent generation trajectories of fashionable clothing for 3models

III. B. 2) Comparison of average curvature of clothing generated by different models

Figure 10 shows the statistical results of the average curvature of clothing generated by the three models. The clothing generated by the model in this paper lost only 19.6% of the wrinkle details at most, which is much lower than the maximum wrinkle detail loss rates of 52.3% and 90.9% of the comparison models. That is, the fashionable clothing generated by the model in this paper is more realistic in terms of fabric wrinkles.

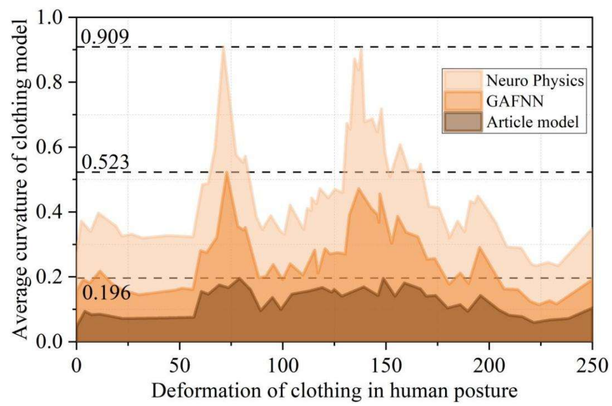

Figure 10: Three models generate the average curvature of the clothing

III. B. 3) Comparison of positional errors between clothing generated by different models and actual clothing

Figure 11 shows the statistical results of the average mesh vertex position error between the clothing generated by the three models and the real clothing data. The average coordinate error of the clothing generated by the model in this paper is only 2.649 units at most, which is smaller than the 8.054 units of Neuro Physics and the 5.311 units of GAFNN, indicating a smaller position error. This also further validates that the point cloud data preprocessing using the ICP algorithm can improve the positional accuracy of the clothing generated by the model.

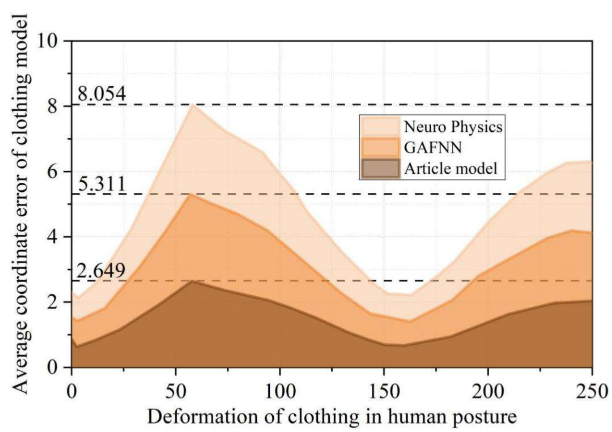

Figure 11: The average grid vertex position error of the clothing

IV. Conclusion

This paper employs the ICP algorithm and particle-spring model to achieve intelligent sustainable fashion design. The ICP algorithm preprocessing stabilizes the error of the three key cross-sections of the garment within 1.5%. Intelligent adjustment takes no more than 10 seconds, significantly less than the 65, 59, and 67 seconds required for manual adjustment, while also improving accuracy. The error between the generated trajectory and the actual trajectory of the garment in this model ranges from 0.10 to 0.30, with an average curvature not exceeding 19.6%, and the maximum position error is only 2.649 units. Future work could focus on developing a degradable fabric parameter library to enhance the sustainability of fashion design and strengthen the environmental benefits of intelligent garment generation.

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