Development of Multimedia-Assisted Clothing Try-On System for Elderly Individuals

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ABSTRACT

With the improvement of living standards, the demand for high-quality, personalized modern fashion has surged, which has promoted the growth of this customized clothing industry. The integration of cutting-edge technologies such as 5G, artificial intelligence and Internet of Things with traditional clothing production has pushed virtual try-on technology to the forefront of global research. This study focuses on the technical challenges of 3D clothing dynamic virtual try-on system in real life—specifically, personalized posture tracking, high-fidelity real-time interaction and cost-effectiveness—using 3D visual sensing theory, clothing simulation modeling principle and advanced tools including Unity3d and Maya. It deeply studies the key areas: collecting sensory data based on Kinect, extracting the skeletal posture characteristics of the elderly, measuring their body circumference and size, developing a 3D dynamic model of clothing with tracking control, and realizing real-time dynamic display of virtual try-on results.

KEYWORDS

Elderly Group, Multimedia Information Technology, 3D Dynamic Virtual Try-On, 3D Clothing Perception Model, GL-SVD Collaborative Tracking Method, GBDT Girth Calibration Model

INTRODUCTION

In recent years, with the improvement of material living standards, people have higher requirements for clothing and accessories and are pursuing higher-end and more personalized fashion products (Yuan et al., 2013). Users' demand for personalized and fashionable products has promoted the development of clothing customization. According to the 2021-2027 China Clothing Industry Operation Situation and Future Development Trend Report, with the continuous improvement of consumers' awareness of personalized products, customization service has gradually become the focus of brand clothing development. In the future, designers will tend to design clothing for individual consumers. The replacement of consumption patterns has gradually upgraded the traditional clothing sales industry, and the change of demand concept has promoted the gradual development of the clothing industry towards interconnection, which is manifested in the closer connection among customers, brand products, and enterprises, showing a new trend of “internet + clothing customization” (Baytar & Ashdown, 2015).

Under the mode of internet consumption, purchasing clothing online has become the primary mode of consumption for young people, and it points to the trend of customized sales in the clothing industry in the future. However, in recent years, the drawbacks of online shopping have gradually

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become prominent, mainly manifested in that customers are not satisfied with the clothes they have purchased, resulting in a high rate of product returns. According to consumer survey research in online shopping, consumers think that it is difficult to understand the actual wearing of clothing in the online clothing purchase process, and there is a lack of experience in trying on clothes, which is the fundamental reason for the high return rate of online shopping. In the shopping mode of the e-commerce platform, customers' cognition of clothing styles relies on clothing information such as pictures, and the display and interaction capabilities of products cannot allow customers to truly feel the experience of wearing clothing on their bodies. In the actual consumption link, the consumers' try-on experience is an important factor that promotes the purchase decision. The offline purchase model also has limitations. In the traditional clothing purchase and customization process, merchants need to assign personnel to guide customers to try on. At the same time, the try-on process is extremely cumbersome, and some customized production processes also require customers It takes a lot of time and cost to go to the site to measure the body for many times (Alzamzami et al., 2023).

Therefore, in order to address the above drawbacks and meet the needs of an efficient clothing try-on experience, virtual clothing try-on technology came into being. This technology integrates clothing selection and human-computer interaction. By providing a personalized virtual clothing model to fit the elderly, it realizes the function of convenient try-on and simplifies the tedious process of the traditional try-on mode. To a certain extent, the experience and realism of the online clothing try-on process are improved. At the same time, with the close integration of the clothing industry with 5G communication, artificial intelligence (AI), augmented reality/virtual reality (AR/VR), and other technologies, clothing virtual try-on technology is gradually developing towards a complete virtual try-on system (Zhu et al., 2018).

From the perspective of existing technology development, virtual try-on technology can be roughly divided into two-dimensional (2D) and three-dimensional (3D) realization methods (Zhang et al., 2019). The 2D-based method is realized by the gesture feature transformation of 2D clothing images, while the 3D-based method completes gesture recognition and clothing coverage by establishing a 3D coordinate mapping relationship. The 2D virtual try-on system has the limitations of insufficient authenticity and dynamics, and the try-on posture is relatively simple, so it cannot meet the real-time and dynamic experience requirements of virtual try-on. The 3D try-on system has advantages in both realism and interactive experience, but the existing 3D virtual try-on system requires 3D high-precision scanning equipment. Usually, the equipment is expensive, and the application cost is too high, so it is not suitable for current demand for a try-on experience in the internet consumption mode. Therefore, with the cross-development of digital clothing and internet consumption patterns, it is of practical value to design a real-time and dynamic low-cost 3D virtual try-on experience test system to satisfy consumers for personalized virtual try-on experience and meaning (Liu et al., 2020).

Although a variety of virtual fitting applications have emerged in the market, Ghodhbani et al (2023) emphasize that the market still needs an affordable and technically mature 3D virtual fitting experience. Therefore, the purpose of this study is to analyze the status and application of current research in China and abroad; focus on the dynamic fitting problems in the process of 3D virtual fitting, and innovatively study the dynamic fitting problems such as posture matching tracking and real-time coverage of clothing fabrics based on the development of existing 3D fitting technology and modeling software; and propose a breakthrough real-time, dynamic, and real-person oriented 3D virtual fitting system. In contrast with previous attempts that sacrifice the level of detail or require expensive equipment, the solution proposed in this paper adopts a novel global learning singular value decomposition (GL-SVD) collaborative tracking method, which significantly improves the tracking accuracy, reduces the relative error rate (see Table 1), and realizes the balance between cost performance and high-fidelity virtual fitting experience without increasing costs.

Table 1. Data records of two tracking methods

	frequency	1	2	3	4	5	6	7	8	9	10
Relative error M(%)	GL-SVD Collaborative tracking method	0.074	0.082	0.071	0.075	0.108	0.092	0.084	0.094	0.076	0.073
	Avatar Bone Control Method	0.146	0.177	0.223	0.168	0.204	0.191	0.203	0.182	0.178	0.188

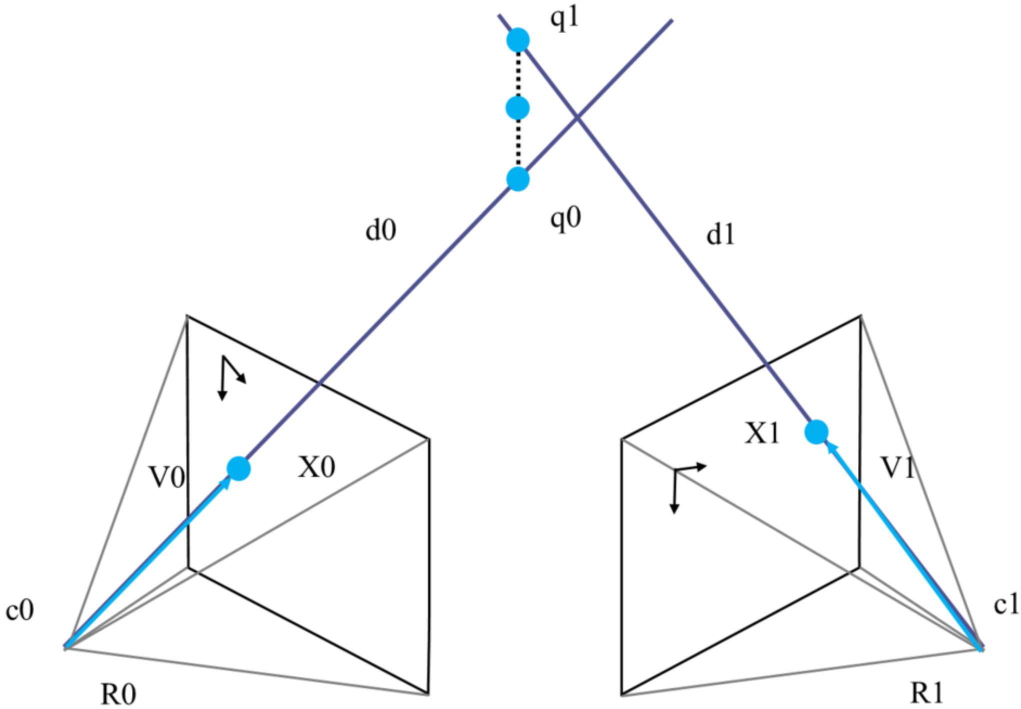
State of the Art

Research outside China on virtual try-on systems has been underway for some time, and the development of 2D virtual try-on technology has improved considerably. For example, Hwangbo et al. (2020) proposed an image pairing method that utilizes a trainable architecture (Conditional Simulation Generative Adversarial Network) for clothing replacement on fashion model photos. Xitong et al. (2022) used a shape context matching algorithm and U-Net generator to realize the try-on of clothing. Hashmi et al. (2020) introduced a convolutional neural network (CNN) architecture with geometric matchers to improve the clothing detail features and improve the generalization ability of the network.

3D virtual try-on technology can realize the try-on effect of coherent posture changes, which is more advantageous in terms of experience. The earlier 3D virtual try-on systems in foreign countries are mostly used in clothing manufacturing. Professional 3D scanners are used to 3D scan the elderly population, collect all the size data of the elderly population, construct digital 3D clothing models, and combine them with clothing computer-aided design (CAD) tools. The try-on effect of looking around is displayed on the artificial avatar for the designer to modify, which has the characteristics of high precision. However, the equipment of the system is expensive and inefficient. The offline 3D virtual try-on system uses various red, green, blue, and depth (RGB-D), infrared laser and other positioning sensors to identify the posture of the elderly group, which can be divided into two categories according to the different objects of the try-on.

1) Trying on clothes by establishing virtual elderly group models. Early representative products such as Fitiquette Company, ULtra Realistic Company, and Total Immersion Company display virtual fitting mirrors. This is shown in Figure 1. By establishing a 3D mapping relationship between the virtual model and the bones of the elderly group, the clothing model can be fitted to the elderly group and displayed on an interactive screen to realize functions such as clothing style selection. However, the reality of the virtual elderly group models is insufficient, and the fitting effect is not realistic enough. In order to improve the realism of virtual models, a facial recognition algorithm can be used to extract real face images, and when combined with virtual elderly group models to try on clothes, the realism is improved, but it still cannot approach the real try-on effect (Liu et al., 2018).

2) Using real people as fitting objects has received much attention in recent virtual fitting research studies. For example, South Korea's FXMirror fitting product can provide real-time feedback on the movement characteristics of the face and body of the elderly group and can display the characteristics of multiple garments using the hierarchical dynamic try-on effect. Wolff & Sorkine-Hornung (2019), based on the Kinect elderly group skeleton point model and clothing anchor point, iteratively corrected the position of the 3D clothing model and realized the dynamic virtual try-on of short skirts for real elderly groups. Foreign research on virtual try-on has become increasingly effective, and products for virtual try-on for real people have gradually become popular and commercialized.



Although the research on virtual try-on technology in China started late, it has developed extremely rapidly. Roy et al. (2022) focused on the study of virtual try-on of 2D images, retaining the texture features of the fabric on the basis of clothing deformation, and repairing the missing features. Area. Zhang et al. (2020) proposed using the DensePoseRCNN model of a single image of the elderly group to predict texture data to realize the transfer of 2D clothing texture features. Although the texture effect of the 2D try-on on the image is becoming more and more realistic, the physical simulation effect of the cloth cannot be realized, and there is still a gap between the real-time and dynamic 3D try-on effect.

Domestic research on 3D virtual try-on based on RGB-D sensors has attracted much attention. The try-on technology proposed by Zhang Xiaoli uses the depth information of the Kinect skeleton point and the gray model to predict the rotation law of the elderly group and uses face detection technology to achieve front, side, and back static try-on functionality (Chu et al., 2022). Hu et al. (2022) used real people as the fitting objects, and based on the Kinect skeleton features, they used the built-in Avatar skeleton control method of the game development engine Unity3d to drive the clothing feature points to follow the skeletal points of the elderly group. Li & Cohen (2021) used Kinect. The 3D data of the elderly group collected and processed by the equipment is used to train the weighted random forest model to predict clothing size, focusing on developing a clothing size recommendation system and testing its effectiveness. Xue Jingya et al. improved the realism by simulating the physical dynamic effect of the cloth and at the same time adjusted the overall size of the clothing model according to the distance of the skeleton points, which improved the close-fitting effect of the clothing fitting. However, the Avatar skeletal control method lacks precision in the degree of fit-in dynamics and pose matching.

In recent years, a large number of virtual try-on products have also appeared in China, such as the fitting environment launched by Tmall, the online app of the Taobao fitting room, and the 3D try-on software researched by domestic universities (Tao et al., 2018). These products are similar to foreign offline fitting environment products. They adopt the method of the 3D elderly group modeling, build virtual elderly group models with the size of the elderly group collected by visual sensors or input by users, and use features such as face images and skin color. Synthesizing a real person virtual image for try-on improves the realism and visual effect of the try-on and promotes the development of domestic virtual try-on technology (Zhao et al., 2021).

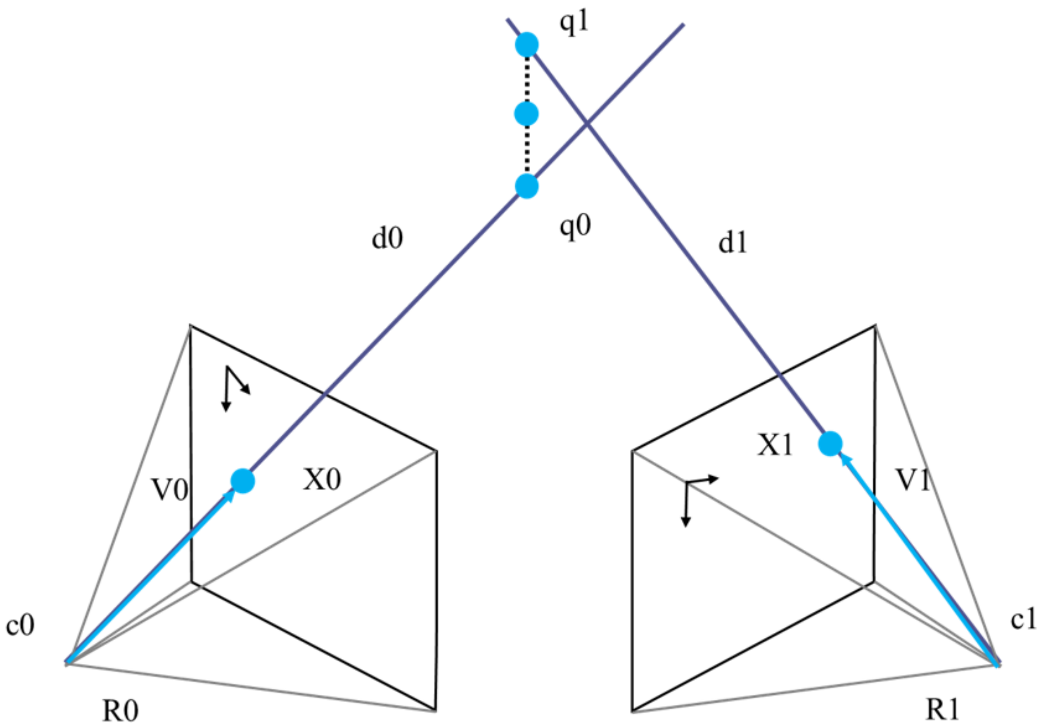
Recently, Yunzhimeng Company, Yimai Technology Company, and Modern Avenue Company have also successfully launched 3D somatosensory magic mirrors, which are used for a real person try-on experience in offline stores. The N-show3D somatosensory mirror developed by New Rhythm Intelligent Technology Co., Ltd. uses a real person as a fitting object for all-round virtual try-on. Users can freely turn their bodies to view the fitting effect. Through somatosensory technology and computer rendering technology, clothing can be realistically fitted on the user's body, and it shows the drape and fluttering effect of the fabric, which promotes the commercial application of virtual try-on for real people in China (Tuan et al., 2021).

Research on the virtual try-on of clothing simulation rendering and partial detail display has also attracted the attention of domestic researchers (Volino et al., 2005). Detail display and quick pattern design improve the efficiency of dress customization. Zhu Qingyan also used CLO Virtual Fashion 3D (CLO3D) software to establish a clothing effect evaluation system to optimize evaluation indicators and patterns in terms of pressure, deformation rate, and contact points, strengthening parts of clothing try-on. Detail design and clothing refinement effect (Huang, 2015).

Despite the proliferation of virtual try-on applications, a significant gap exists in the market for affordable yet sophisticated 3D virtual try-on experiences (Ghodhbani et al., 2023). To clarify the term “low-cost,” our approach significantly reduces hardware dependence compared to traditional high-precision 3D scanning systems, which typically incur substantial upfront and operational costs. By leveraging advancements in machine learning algorithms and optimizing computational processes, we achieve a reduction in infrastructure expenses without compromising on the realism or interactivity that consumers expect. This constitutes a pivotal distinction from prevailing solutions, marking a departure from the cost-prohibitive nature of traditional 3D try-on technologies. Therefore, the research goal of this paper is based on the current research status and application background at home and abroad, focusing on the dynamic try-on problem in 3D virtual try-on. On the basis of the existing 3D try-on technology and the development of modeling software, the tracking of pose matching innovative research on dynamic try-on problems such as real-time coverage of clothing fabrics. Our paper presents a ground-breaking, real-time, and dynamic 3D virtual try-on system tailored for real individuals. Unlike previous attempts that either compromised on the level of detail or required expensive equipment, our solution harnesses a novel GL-SVD collaborative tracking method, which significantly enhances the tracking accuracy by reducing the relative error rate (as shown in Table 1) without incurring additional costs. This technical advancement represents a leap forward in achieving a balance between affordability and high-fidelity virtual try-on experiences (Sharma, 2020).

Our 3D virtual try-on system pioneers a new frontier in personalized and immersive virtual fitting experiences, particularly catering to the elderly demographic with its high realism and adaptive pose-matching capabilities. By addressing the crucial challenge of real-time fabric coverage during dynamic movements, we have not only bridged the gap in the availability of affordable yet high-quality 3D try-on platforms but have also pushed the boundaries of what is achievable in terms of dynamics and user engagement. This study’s principal contribution lies in demonstrating the viability of a cost-effective system that simultaneously enhances the authenticity and interactivity of virtual try-ons, thereby enriching the consumer experience in the digital clothing and internet consumption era. Our work underscores the potential for democratizing access to advanced virtual try-on technology and fostering a more inclusive and engaging online retail landscape.

Figure 2. Schematic diagram of triangulation



METHODOLOGY

Difficulties in Virtual Try-on for Elderly Groups

One challenge in virtual try-on technology is related to the uncertainty of the target characteristics of elderly groups. Changes of posture and movement of the elderly group are irregular, and it is difficult to use a unified conceptual standard to describe the movement of the elderly group, which makes it difficult to classify the posture (Yan et al., 2022). At the same time, the movement of the elderly is characterized by the coordinated movement of the trunk and the limbs. There are both connections and differences between them. Compared with the trunk, the limbs are more flexible, which requires higher accuracy of the pose matching algorithm. At the same time, because the dynamic try-on of clothing needs to deal with the detail changes in the local area of the elderly group, it is necessary to overcome the interference of external environmental factors such as light level, contrast, and the color of the elderly group's own clothing. There are certain requirements for the robustness of the algorithm.

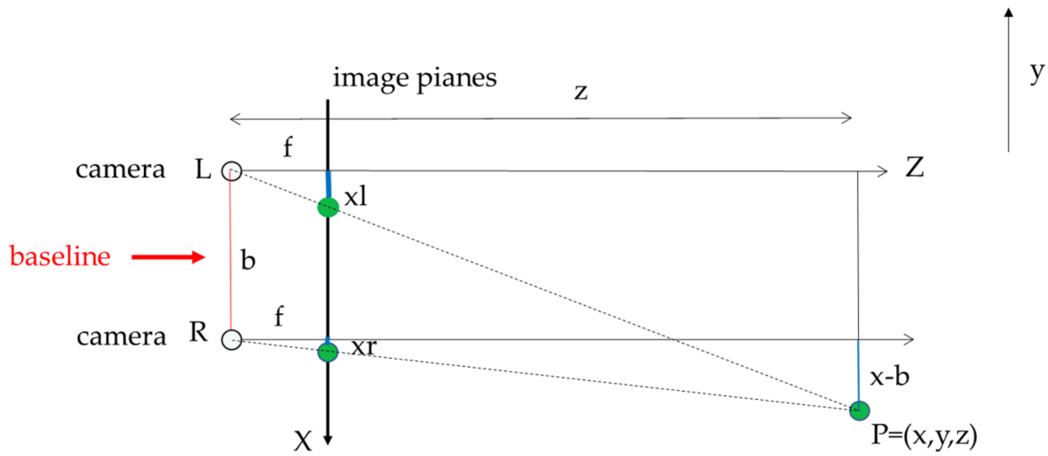
The closer the spatial point is to the imaging plane, the brighter the grayscale value. The schematic diagram of triangulation is shown in Figure 2, and the schematic diagram of binocular stereo vision is shown in Figure 3.

According to the law of similarity of triangles, we have equation (1).

$$\frac{z}{f} = \frac{x}{xl} = \frac{x-b}{xr} \tag{1}$$

Based on equation (1), we get equations (2) and (3).

Figure 3. Schematic diagram of binocular stereo vision



$$x = \frac{xl * b}{xl - xr}, z = \frac{b^* f}{xl - xr} \tag{2}$$

$$z = \frac{b^* f}{d}, x = \frac{z^* xl}{d} \tag{3}$$

Principle of 3D Registration Based on SVD

Three-dimensional registration is used to solve the problem of coordinate mapping from one 3D coordinate system to another 3D coordinate system. Usually, the SVD singular value decomposition method is used for the matching calculation of 3D point sets, and there is the conversion relationship shown in equation (4).

$$Q_j = R \cdot P_i + T + N_i \tag{4}$$

where R is the rotation matrix, T is the translation matrix, and Ni is the noise vector. The matrix and T translation matrix are unknown and need to be solved by SVD method. To do this, first find the centroids of the two 3D point sets, as shown in equation (5).

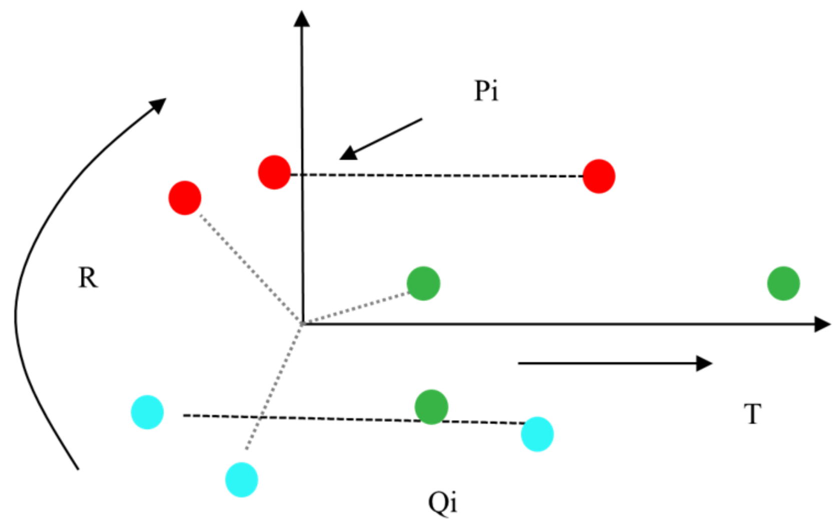
$$P_o = \frac{1}{n}\sum_{i=1}^{n} P_i, Q_o = \frac{1}{n}\sum_{j=1}^{n} Q_j \tag{5}$$

Next, find the displacement vector of each 3D data point with respect to the centroid, as shown in equation (6).

$$P = P_i - P_0, Q = Q_j - Q_0 \tag{6}$$

Then, calculate the correlation matrix H of two-point sets using the centroid displacement vector, as shown in equation (7).

Figure 4. Schematic diagram of point set registration



$$H = \sum_{i=1}^{n} P Q^T \tag{7}$$

H (correlation matrix) represents the correlation of the coordinates of two-point sets and performs SVD decomposition on the H matrix, as shown in equation (8).

$$H = USV^T \tag{8}$$

Matrices U, S, and V are orthogonal matrices in the decomposition process. For matrix R, the optimal solution is shown in equation (9).

$$R = VU^T \tag{9}$$

Verify that the optimal solution is valid: if det(R)=1, the matrix R is calculated correctly, otherwise, if det(R)= -1, the R calculation is invalid. When R is calculated correctly, the translation matrix T can be calculated from R, as shown in equation (10).

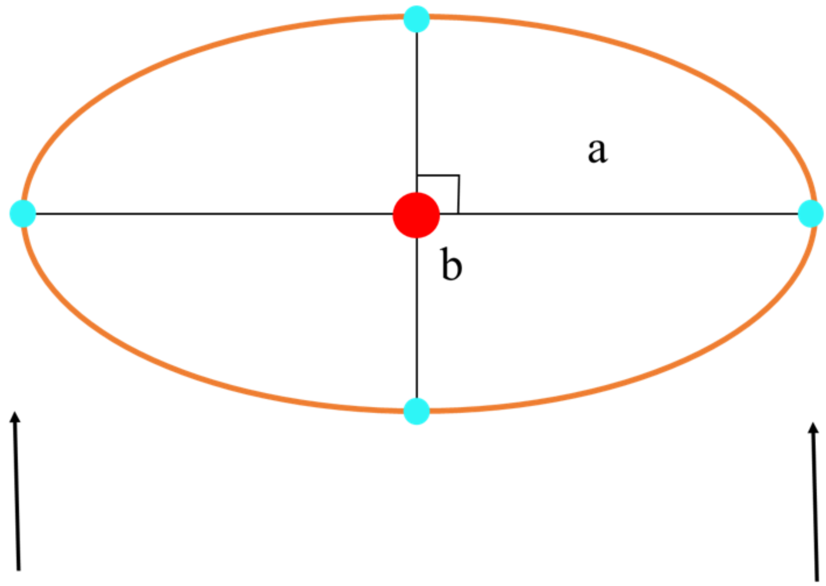
$$T = -R * P_0 + Q_0 \tag{10}$$

The conversion diagram of two 3D point sets {Pi} and {Qj} is shown in Figure 4.

Gradient Boosting Decision Tree (GBDT)

In this study, we propose a gradient boosting decision tree (GBDT)-based girth calibration model (Friedman, 2001), which aims to enhance the accuracy and robustness of predicting the girth measurements of trees in forestry management. GBDT, known for its strong predictive power and ability to handle complex non-linear relationships, is employed to incrementally build an ensemble of decision trees by iteratively improving the residuals from previous models. This approach not only captures subtle variations in tree girth data but also effectively deals with potential outliers and missing values, ensuring a high level of precision in our calibration.

Figure 5. Schematic diagram of the ellipse model



Because the characteristic size of circumference such as bust circumference and waist circumference cannot be calculated directly by the distance between a single point, it must be extracted by combining the edge feature points of the elderly group and the circumference of the silhouette. Therefore, this paper adopts the method of size fitting to calculate the circumference of the elderly group size. In the reconstruction of the 3D elderly population model, the horizontal section of the elderly population can be approximated as an ellipse model, and the circumference size is the ellipse circumference. It only needs to measure the semi-major axis and semi-minor axis to calculate the ellipse perimeter. Figure 5 shows a schematic diagram of the ellipse model.

The formula for calculating the circumference is shown in equation (11).

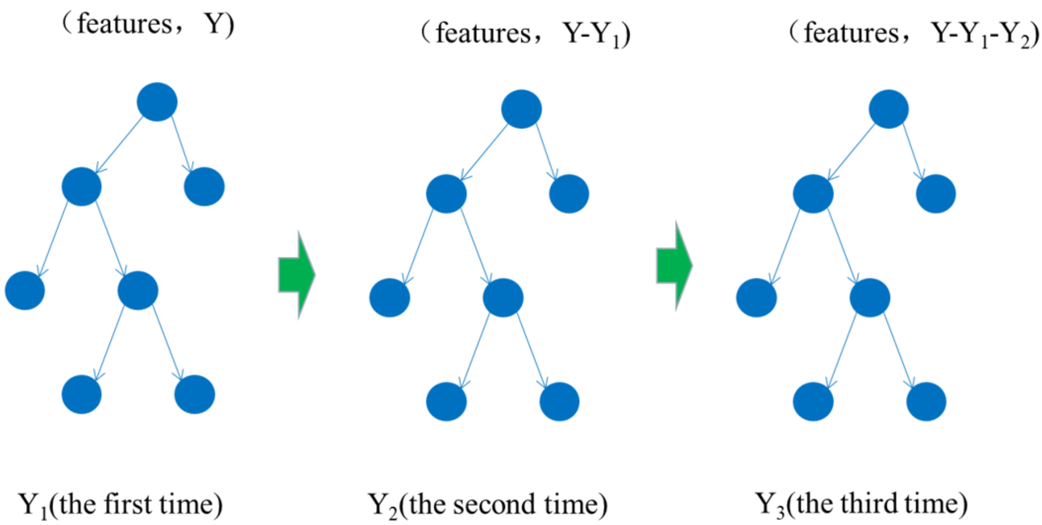
$$L = 2\pi\sqrt{\frac{a^2 + b^2}{2}} \tag{11}$$

Taking the chest circumference as an example, the elderly group is divided along the horizontal section; at this time, the section of the chest area approximates an ellipse model. Based on the contour extraction method of the elderly population, and the RGB-D data collected by Kinect, the circumference feature size is fitted, and the chest width length and chest thickness depth are obtained by traversing the pixels in this range, so as to calculate the circumference of the chest ellipse.

Because there is still a certain error Y between the circumference of the ellipse and the real bust size, for people with unbalanced body shapes, it is not accurate to obtain the size of the circumference only based on the characteristics of a small number of elderly groups. Therefore, in order to improve the fitting accuracy of the girth feature, this paper combines the ellipse model and the GBDT algorithm to add the initial girth perimeter calculated by the ellipse perimeter formula to the error value fitted by the GBDT algorithm to establish the GBDT girth calibration model. Calibrating the accuracy of girth dimensions reduces fitting errors. The calculation formula in equation (12) of the circumference dimension P after calibration is as shown in equation (13).

$$P = P_i + Y_o \tag{12}$$

Figure 6. Fitting process of GBDT algorithm



$$Y_o = \sum_{i=1}^{n} Y_i \tag{13}$$

In equations (12) and (13), Y_o is the fitting value of the GBDT algorithm to the girth size error Y, and Y_i represents the result of each round of training. P_i is the initial girth perimeter.

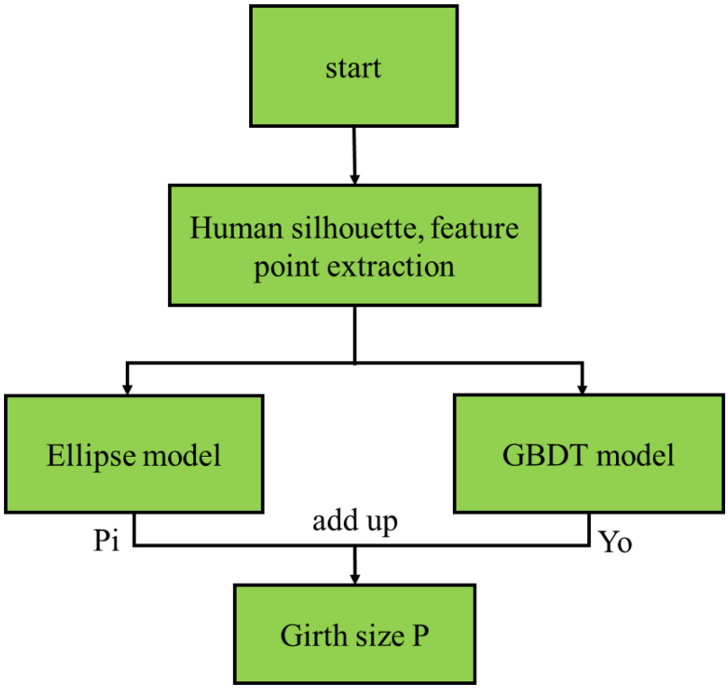
In order to improve the robustness of model accuracy calibration, multiple features such as section width, section thickness, height, shoulder width, and arm length are used for model training. The training data set is obtained with reference to the MPII human shape elderly population model data. The error training and fitting process of the GBDT algorithm is shown in Figure 6. Figure 7 shows the flow chart of the GBDT calibration model. Figure 8 shows the results of girth size fitting and calibration performed by the GBDT calibration model. The real value in the figures is the 100 girth size data of the validation set in the training data set.

Focusing on the problem of feature collection in the elderly group area, based on the technical principle of the Kinect somatosensory device, the research and realization of the extraction method of the RGB-D and bone information of the elderly group is carried out. By collecting the original feature data of the elderly population, a method for pixel clustering based on the local feature similarity of gradient and depth is proposed, which satisfies the efficiency and accuracy of the silhouette recognition and width size calculation of the elderly population. At the same time, the proposed GBDT girth calibration model, combined with the ellipse formula and GBDT fitting algorithm, is used to calibrate the girth size of the elderly population, which effectively improves the accuracy of girth size fitting.

Introduction of Related Methods and Equipment

With the in-depth application of personalized and intelligent technology in the field of clothing customization, accurate acquisition of human body size information has become the key to enhancing user experience. This section introduces two core technologies: time of flight (TOF) method and Kinect somatosensory device, which play an important role in the virtual try-on system of clothing customization for the elderly.

Figure 7. GBDT calibration model flow chart



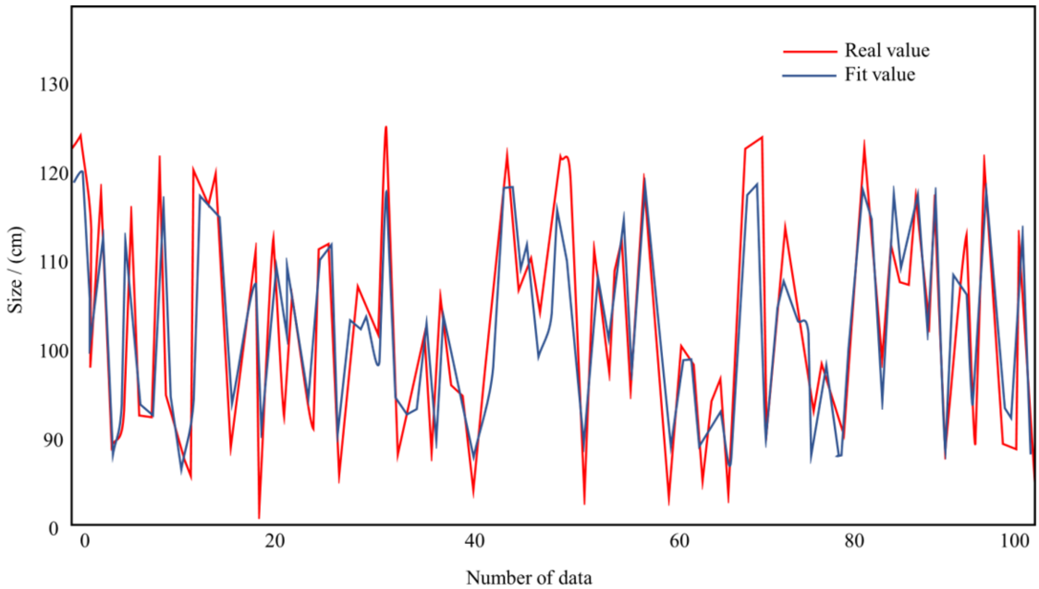
TOF Method

TOF method is a technology to obtain the depth information of an object by calculating the flight time of optical pulses. This technology has been widely used in many applications, such as mobile phones, automobiles, games, logistics monitoring and so on, because of its simple equipment structure, easily integrated implementation, fast response, good ranging performance in strong light and weak light environments, low power consumption, and low cost. TOF technology provides technical support for high-precision body size measurement by continuously sending or modulating light pulses to objects and recording the reflected light pulses, and accurately measuring the distance by using this information.

Kinect Somatosensory Equipment

Kinect somatosensory device introduced by Microsoft as an RGB-D visual sensor was originally designed for motion sensing in Xbox games to realize human-computer interaction control. It integrates a color camera, a depth camera, and an infrared transmitter, which can obtain the resolution and depth information of the image with high accuracy and support voice control. Kinect not only has the function of motion posture estimation and tracking, but also its bone recognition technology is based on the machine learning model on the depth image dataset, which is specially trained for the elderly and can effectively identify and track human bone points. Using TOF technology, Kinect can measure the depth data of object pixels and construct high-resolution depth images, which is of great significance for 3D reconstruction and target ranging. In addition, Kinect equipment is equipped with software development kit (SDK) 2.0 driver application programming interface (API), which can identify and track the dynamic characteristics of multiple elderly people at the same time and

Figure 8. GBDT model girth calibration results



realize interactive control, which further highlights its advantages in identifying the characteristics of elderly people. This study combines the data collection function of Kinect to develop a virtual fitting system for the elderly, aiming at solving the problem of high return rate caused by the lack of fitting experience in online shopping.

Modeling Principle of Clothing Simulation Design for the Elderly

Clothing simulation design mostly uses 3D simulation software such as CLO3D, clothing CAD, and Maya. According to the different materials and characteristics of the physical clothing style, the cloth effect is simulated with 2D clothing pieces, and a network of patterns is established through cutting, processing, and splicing. The mesh model is worn on the virtual model for simulation, and the 3D simulation clothing is obtained. The cloth effect of the simulation clothing can also be displayed by computer rendering tools. Fashion custom design also often uses real-life 3D volume scan data to input clothing simulation design software to adjust the size of virtual models or artificial mannequins. By controlling the mouse, the virtual model can be manually rotated, the limb joints can be rotated, and the clothing can be adjusted by pulling the grid points on the clothing grid mold in the picture. The styles of clothing simulation design mostly come from the styles of physical clothing, such as clothing manufacturers, e-commerce sales websites, and clothing brand conferences.

In the modeling stage of 3D simulation clothing, the structure, proportion, profile and other characteristics of clothing styles need to be considered. According to different clothing characteristics, the effect of virtual try-on of clothing is also different. Among them, the design of clothing structure needs to present the beauty of the body curve of the elderly group, not only to highlight the advantages of the elderly group's body shape, but also to hide the shortcomings of local body shapes to enhance the temperament of the wearer. The design of proportions, such as the size ratio of the neckline, the ratio of the length of the upper and lower body, and the ratio of the width, and width of the measurements, will all affect the overall effect of the virtual try-on. In addition, as the primary link of clothing design, clothing silhouette is affected by the looseness and size of shoulders, chest, waist, hips, and bottom hem, which reflects the overall impression of clothing shape and is the basis for the beauty of clothing.

In the virtual try-on experience, the size of the 3D simulation clothing should be adapted to the body shape and profile structure of the elderly group, that is, to meet the needs of fit. The degree of fit means that the clothing can smoothly show the shoulders, chest, waist, and buttocks of the elderly after being dressed, and at the same time ensure that each part has a certain amount of relaxation. The size of clothing generally includes three aspects: vertical, horizontal, and girth. Among them, the horizontal mainly refers to the horizontal width such as shoulder width and chest width, and the fabric coverage is based on the horizontal width of the trunk and limbs of the elderly; the vertical mainly refers to the length of the garment, trouser length, sleeve length, and other vertical lengths, depending on the style and type of clothing; the longitudinal length of the cloth covering the torso and limbs of the elderly group is also different. The circumference refers to the chest circumference, waist circumference, and hip circumference of the elderly group. The length of one circle of the cross-section, the girth characteristics, of the elderly group should correspond one-to-one with the girth characteristics of the simulated clothing.

AR technology is a new technology that integrates computer graphics and sensors. It has been proposed that advanced AR systems simulate the sensory experiences of the elderly, including vision, smell, and hearing, with high fidelity through sophisticated computer rendering techniques, integrating this virtual content seamlessly with the physical world (Al-Ansi et al., 2023). AR technology has three characteristics: the fusion of virtual and reality, real-time interaction, and tracking registration. Its interactive information can be in various forms, including images, sounds, and texts. It can retrieve information features in the real environment and use computer simulations to form relevant virtual data. At the same time, virtual data can generate real-time interaction with the real environment according to the user's body position and movement changes, showing the practicability and timeliness of information interaction.

RESULTS, ANALYSIS, AND DISCUSSION

Test Method and Test Content

This section aims to verify the accuracy of the GBDT girth calibration model proposed in this paper in the prediction of trunk size (chest girth, waist girth, and hip girth) of the elderly population through specific examples and compare its performance with the linear regression algorithm and ellipse model fitting method commonly used in the literature. In order to ensure the comprehensiveness and reliability of the test, we have designed the following detailed test procedures and evaluation criteria.

Overview of Test Process

Sample Selection

Ten elderly people were selected as fitting models, and their actual trunk circumference data were recorded, including chest circumference, waist circumference and hip circumference, as shown in Table 2. This data represents the true size distribution of the target user group, which provides a basic basis for the subsequent model verification.

Model Application

Each experimenter uses the GBDT calibration model, linear regression algorithm, and elliptic model to make three independent prediction calculations for the girth data of these 10 models. After each prediction, the average of the three results is taken as the final prediction output to reduce the influence of random error. This data is summarized in Table 3.

Table 2. True torso circumference size

Numbering	1	2	3	4	5	6	7	8	9	10
chest circumference/cm	108	93	86	82	102	95	84	87	80	90
waistline/cm	91	84	72	75	83	90	67	71	68	72
hip circumference/cm	97	88	85	79	94	91	82	88	77	85

Table 3. Data records of three fitting methods

GBDT calibration model	Numbering	1	2	3	4	5	6	7	8	9	10
	chest circumference/cm	106.3	92.8	81.8	78.5	106.1	90.2	87.5	85.0	85.5	87.2
	waistline/cm	92.3	82.3	70.4	72.0	77.7	91.6	62.0	76.1	67.2	72.6
	hip circumference/cm	95.6	91.4	88.4	75.5	97.0	87.4	85.2	89.1	77.9	84.9
Linear Regression Algorithm	Numbering	1	2	3	4	5	6	7	8	9	10
	chest circumference/cm	116.6	101.3	76.8	72.7	91.7	84.3	74.0	96.1	72.4	98.4
	waistline/cm	98.9	74.2	80.0	64.6	91.3	97.7	76.4	60.8	57.4	79.7
	hip circumference/cm	86.2	78.8	76.8	69.1	102.4	82.5	73.8	79.9	67.5	77.4
Ellipse model	Numbering	1	2	3	4	5	6	7	8	9	10
	chest circumference/cm	118.1	83.5	97.7	72.8	93.1	104.0	75.7	97.4	68.6	1001.1
	waistline/cm	81.6	95.6	82.8	65.6	72.2	100.4	58.4	61.3	59.6	83.5
	hip circumference/cm	105.7	80.0	76.2	70.0	103.3	99.5	74.3	97.5	85.8	93.3

Accuracy Evaluation

Based on the actual girth data in Table 2 and the prediction results in Table 3, the mean absolute error (MAE) and root mean square error (RMSE) of the three models are calculated to quantify the prediction accuracy, as shown in Table 4. Meanwhile, Figures 9–11 show the comparison of relative errors of each girth size prediction, which directly reflects the performance differences of different models.

Definition of Evaluation Criteria

MAE refers to the average value of absolute error between the predicted value and the real value and is shown in equation (14).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|N_i - N\right| \tag{14}$$

RMSE measures the magnitude and dispersion of the deviation between the predicted value and the real value and is shown in equation (15).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(N_i - N\right)^2} \tag{15}$$

Description of Test Scenario

In the GBDT calibration model, the gradient lifting decision tree algorithm is used to adjust the parameters of the prediction model according to historical data, so as to approach the actual size.

Table 4. Accuracy evaluation results

	GBDT Calibration Mode	Linear Regression Algorithm	Ellipse Model
chest circumference	**MAE:4.2RMSE:4.5**	**MAE:7.8RMSE:9.1**	**MAE:8.6RMSE:9.9**
waistline	MAE:3.8RMSE:4.1	MAE:8.3RMSE:8.8	MAE:8.9RMSE:9.2
hip circumference	MAE:5.1RMSE:5.3	MAE:7.4RMSE:8.2	MAE:8.2RMSE:8.8
mean	MAE:4.3RMSE:4.6	MAE:7.8RMSE:8.7	MAE:8.5RMSE:9.3

Figure 9. Comparison of bust size fitting results

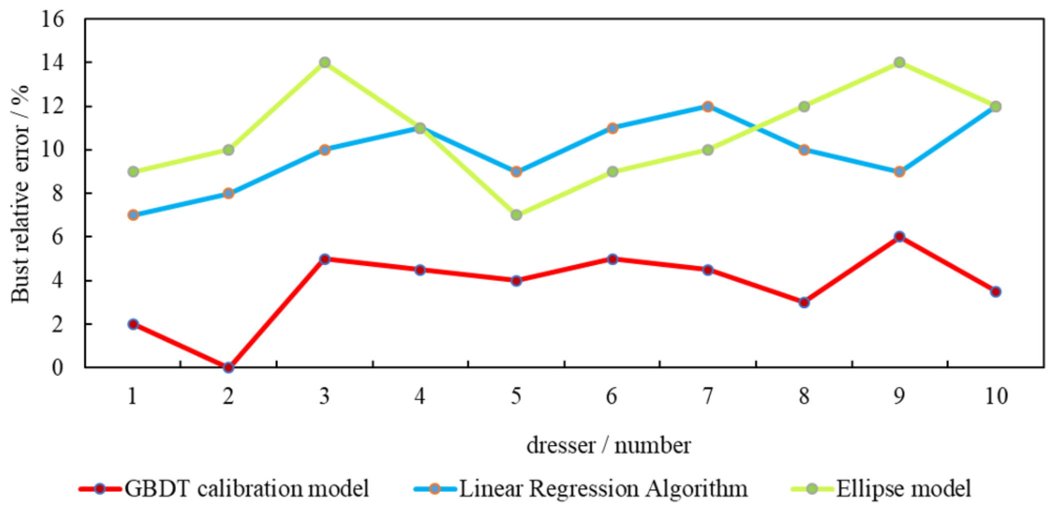


Figure 10. Comparison of waist size fitting results

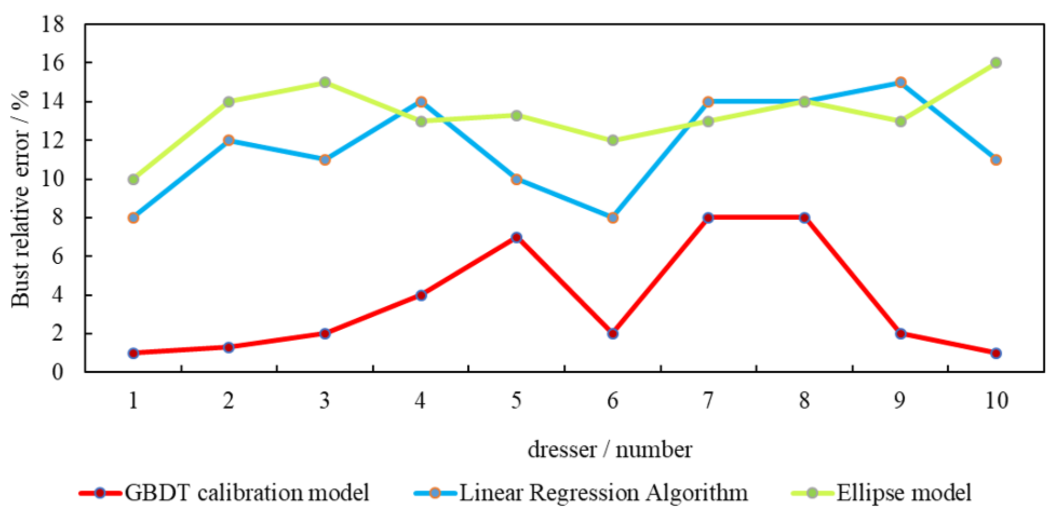
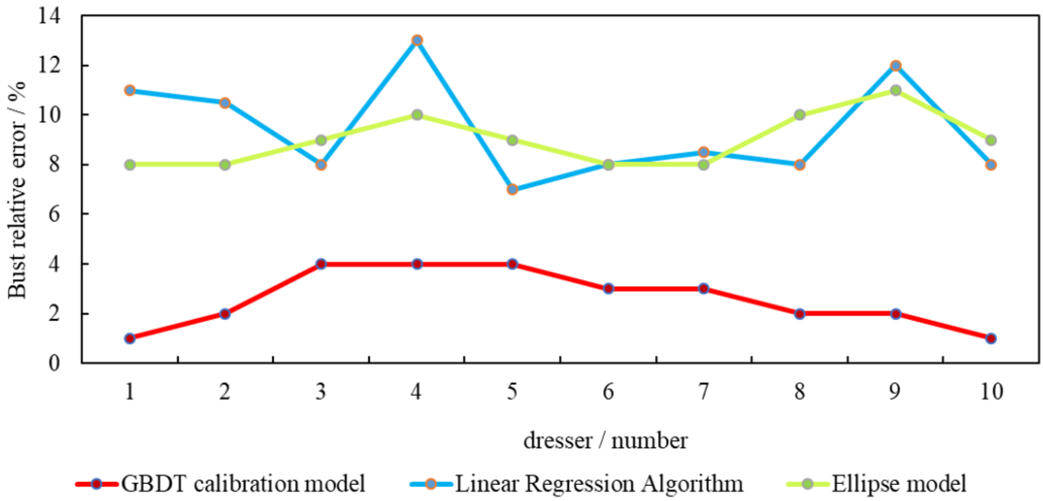


Figure 11. Comparison of fitting results of hip size



The linear regression algorithm is based on the principle of least square method, and the linear relationship model between girth size and potential factors is established.

Elliptic model fitting simulates human body shape and calculates the circumference size through the geometric characteristics of ellipse.

Taking the girth and dimension features of the trunk of the elderly population (chest, waist, and hip) as an example, the accuracy of the GBDT girth calibration model method proposed in this paper is compared with the linear regression algorithm in the literature and the ellipse model fitting method in the literature. The evaluation indicators are:

(1) MAE, which refers to the average of the absolute value of the error between the fitted value and the true value. It is shown in equation (14).
(2) RMSE, which measures the deviation and dispersion between the fitted value and the true value, as shown in equation (15).

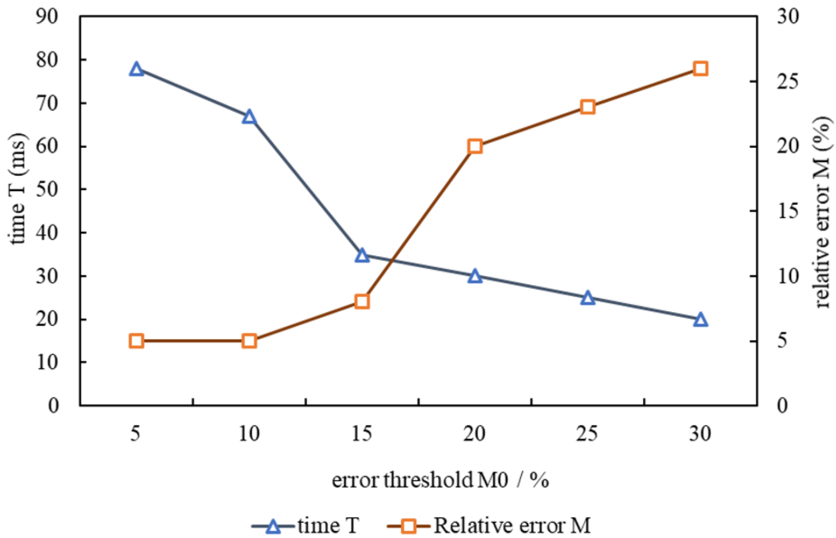
By fitting the torso circumference size of 10 fitters, each experimenter used the above three methods to calculate 3 times respectively, and the fitting results of each method took the mean value of the three calculations and recorded them in Table 3. Table 2 is the real circumference size of 10 people who try on clothes. Table 4 shows the accuracy evaluation results of the three methods. Figures 9–11 are the relative error comparisons of the three methods for girth size fitting.

The analysis of the experimental data and the fitting curve shows that, compared with the ellipse model fitting method in the literature and the linear fitting method in the literature, the proposed method in this paper is more accurate. The MAE of the GBDT girth calibration model for girth fitting is 4.3, and the RMSE is 4.6. The overall error is smaller, so it can ensure that the clothing model can more accurately match the body structure and contour of the elderly population. The shape features improve the fit and personalized experience of virtual try-on.

Dynamic Tracking Accuracy and Real-Time Optimization

The tracking error threshold M0 affects the accuracy and real-time performance of dynamic feature point tracking. This section takes the tracking of the wrist dynamic feature points as an example and uses six groups of different thresholds M0 to carry out comparative experiments. The evaluation

Figure 12. Tracking accuracy and real-time analysis



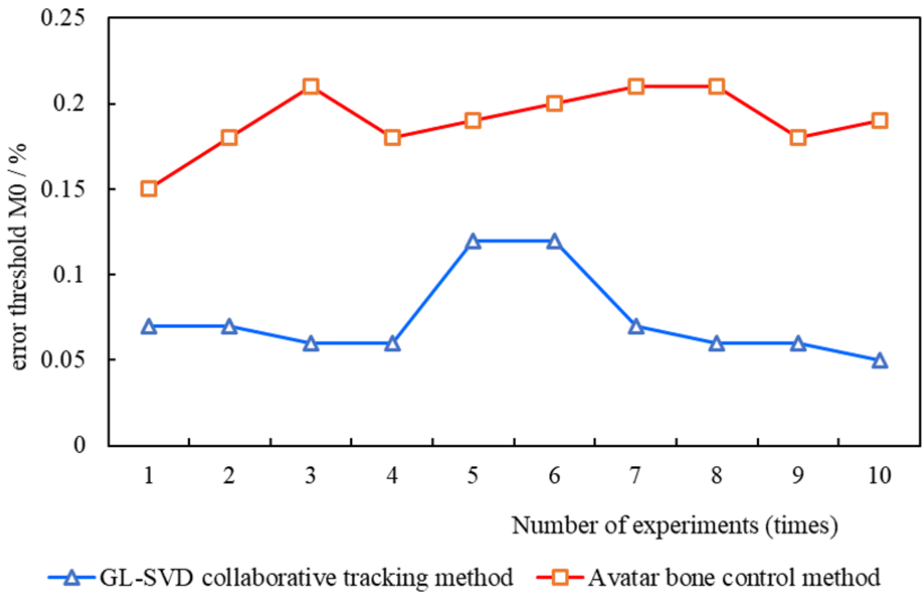
index is the calculation formula of the relative tracking error M and the algorithm iteration time T, M, and the relative error mean and iteration of the 10 tracking process are taken. The time mean is taken as the result of each group of experiments. Figure 12 shows the relative tracking accuracy M and the iterative calculation time T, respectively, changing with the threshold M0.

According to Figure 12, M and M0 are positively correlated, indicating that when the error threshold M0 decreases, the relative error M also decreases, and the tracking accuracy of the system improves. However, T and M0 are negatively correlated, indicating that when the error threshold M0 decreases, the system needs to iterate more times to meet the requirements of tracking accuracy, so the iteration time T increases. Therefore, in order to ensure the high precision and less iteration time of the collaborative tracking method, this paper takes the tracking error threshold M0 = 15% as the optimal value. Taking the dynamic tracking of the central feature point of the spine as an example, the accuracy of the GL-SVD collaborative tracking method proposed in this paper and the Avatar bone control method are compared. The evaluation index is the relative tracking error M, and Table 1 shows the data records of the two tracking methods. Figure 13 shows the performance comparison results of the relative tracking error M. When the fitting person moves, the image frames at a certain moment are randomly captured for comparison.

The comparison shows that the traditional Avatar skeleton control method has a slow response and shows a large clothing position deviation. Compared with the Avatar method, the GL-SVD collaborative tracking method proposed in this paper reduces the relative tracking error M by about 10%, and the tracking accuracy is significantly improved. GL-SVD has the advantages of fast and accurate performance, so it can ensure the real-time and precision requirements of dynamic tracking of clothing models and improve the dynamic experience of virtual try-on.

Based on the above findings, our research not only achieved a breakthrough in technology, but also made substantial progress in user experience. By enhancing the real-time, dynamic adaptability and accuracy of clothing coverage, our system provides an effective way to solve the problem of insufficient online shopping experience and reduce the return rate. The research proves that technological innovation and optimization of user experience can better serve the aging society, promote the healthy development of the digital clothing consumer market, and open a new path for the popularization and inclusive application of virtual fitting technology.

Figure 13. Tracking accuracy comparison



CONCLUSION

By developing and verifying an innovative GL-SVD collaborative tracking method, this study significantly improves the real-time, dynamic adaptability and accuracy of the virtual fitting experience system and provides an effective way to solve the problem of high return rate of online shopping. Compared with the traditional Avatar bone control method and girth size adaptation method, the MAE of this method is reduced by 10% to 4.3, and the RMSE is reduced to 4.6, which is superior to other comparison methods. This shows that the clothing perception model we built can realize the dynamic real-time tracking of the height matching between clothes and the real human body, adapt to the needs of personalized body shape and various dynamic postures, and enhance the fabric coverage and realism.

More importantly, the system not only achieved a breakthrough in technology, but also made substantial progress in user experience. By constructing a virtual fitting demonstration and comparative test environment based on the Windows 10 operating system, the dynamic fitting effects of seven postures, four clothing types and two body contours for the elderly in various fitting scenes are demonstrated, which proves the real-time dynamic characteristics and wide applicability of the system. In addition, the GBDT circumference calibration model proposed in this study further improves the authenticity and personalization level of fitting by accurately matching the torso circumference (chest circumference, waist circumference and hip circumference).

Ultimately, this study not only enriches the application practice of virtual reality and AR technology in the clothing industry, but it also provides technical support for the development of Internet Plus's clothing customization model in the future. By providing a low-cost, high-efficiency solution, it meets the growing demand of consumers for personalized and dynamic fitting experience, promotes the transformation and upgrading of the clothing industry to a more intelligent and interactive direction, and is of great value to promoting the customer satisfaction of e-commerce platforms and reducing operating costs.

CONFLICTS OF INTEREST

The author declares that she has no conflicts of interest.

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REFERENCES

Al-Ansi, A. M., Jaboob, M., Garad, A., & Al-Ansi, A. (2023). Analyzing augmented reality (AR) and virtual reality (VR) recent development in education. *Social Sciences & Humanities Open*, *8*(1), 100532. 10.1016/j.ssaho.2023.100532

Alzamzami, O., Ali, S., Alkibsi, W., Khan, G., Babour, A., & Bitar, H. (2023). Smart fitting: An augmented reality mobile application for virtual try-on. *Romanian Journal of Information Technology and Automatic Control*, *33*(2), 103–118. 10.33436/v33i2y202308

Baytar, F., & Ashdown, S. (2015). An exploratory study of interaction patterns around the use of virtual apparel design and try-on technology. *Fashion Practice*, *7*(1), 31–52.

Chou, C. L., Chen, C. Y., Hsieh, C. W., Shuai, H. H., Liu, J., & Cheng, W. H. (2021). Template-free try-on image synthesis via semantic-guided optimization. *IEEE Transactions on Neural Networks and Learning Systems*, *33*(9), 4584–4597. 10.1109/TNNLS.2021.305837933635797

Chu, C. H., Chen, Y. A., Huang, Y. Y., & Lee, Y. J. (2022). A comparative study of virtual footwear try-on applications in virtual and augmented reality. *Journal of Computing and Information Science in Engineering*, *22*(4), 041004. 10.1115/1.4053328

Friedman, J. H. (2001). Greedy function approximation: A gradient boosting machine. *Annals of Statistics*, *29*(5), 1189–1232. 10.1214/aos/1013203451

Ghodhbani, H., Neji, M., Qahtani, A. M., Almutiry, O., Dhahri, H., & Alimi, A. M. (2023). Dress-up: Deep neural framework for image-based human appearance transfer. *Multimedia Tools and Applications*, *82*(15), 23151–23178. 10.1007/s11042-022-14127-w36404934

Hashmi, M. F., Ashish, B. K. K., Keskar, A. G., Bokde, N. D., & Geem, Z. W. (2020). FashionFit: Analysis of mapping 3D pose and neural body fit for custom virtual try-on. *IEEE Access : Practical Innovations, Open Solutions*, *8*, 91603–91615. 10.1109/ACCESS.2020.2993574

Hu, B., Liu, P., Zheng, Z., & Ren, M. (2022). SPG-VTON: Semantic prediction guidance for multi-pose virtual try-on. *IEEE Transactions on Multimedia*, *24*, 1233–1246. 10.1109/TMM.2022.3143712

Huang, S. (2015). *Customized 3D clothes modeling for virtual try-on system based on multiple kinects* [Unpublished doctoral dissertation]. Université d'Ottawa/University of Ottawa.

Hwangbo, H., Kim, E. H., Lee, S. H., & Jang, Y. J. (2020). Effects of 3D virtual “try-on” on online sales and customers’ purchasing experiences. *IEEE Access : Practical Innovations, Open Solutions*, *8*, 189479–189489. 10.1109/ACCESS.2020.3023040

Li, C., & Cohen, F. (2021). In-home application (App) for 3D virtual garment fitting dressing room. *Multimedia Tools and Applications*, *80*(4), 5203–5224. 10.1007/s11042-020-09989-x

Liu, K., Zeng, X., Bruniaux, P., Tao, X., Yao, X., Li, V., & Wang, J. (2018). 3D interactive garment pattern-making technology. *Computer Aided Design*, *104*, 113–124. 10.1016/j.cad.2018.07.003

Liu, Y., Liu, Y., Xu, S., Yuan, J., Sun, X., Cheng, K., . . . Tanaka, J. (2020). 3D virtual try-on system using personalized avatars: Augmented walking in the real world. *Proceedings of the thirteenth international conference on advances in computer-human interactions (ACHI 2020)*. International Academy, Research, and Industry Association (IARIA). https://www.proceedings.com/content/057/057119webtoc.pdf

Roy, D., Santra, S., & Chanda, B. (2022). LGVTON: A landmark guided approach for model to person virtual try-on. *Multimedia Tools and Applications*, *81*(4), 5051–5087. 10.1007/s11042-021-11647-9

Sharma, S. (2020). Implementation of a garment and fashion interactive-design system: Towards co-design platform shared with consumers, designers and manufacturers [Unpublished doctoral dissertation]. Centrale Lille Institute.

Tao, X., Chen, X., Zeng, X., & Koehl, L. (2018). A customized garment collaborative design process by using virtual reality and sensory evaluation on garment fit. *Computers & Industrial Engineering*, *115*, 683–695. 10.1016/j.cie.2017.10.023

Tuan, T. T., Minar, M. R., Ahn, H., & Wainwright, J. (2021). Multiple pose virtual try-on based on 3D clothing reconstruction. *IEEE Access : Practical Innovations, Open Solutions*, *9*, 114367–114380. 10.1109/ACCESS.2021.3104274

Volino, P., Cordier, F., & Magnenat-Thalmann, N. (2005). From early virtual garment simulation to interactive fashion design. *Computer Aided Design*, *37*(6), 593–608. 10.1016/j.cad.2004.09.003

Wang, Z., Xing, Y., Wang, J., Zeng, X., Yang, Y., & Xu, S. (2022). A knowledge-supported approach for garment pattern design using fuzzy logic and artificial neural networks. *Multimedia Tools and Applications*, *81*(14), 1–21. 10.1007/s11042-020-10090-6

Wolff, K., & Sorkine-Hornung, O. (2019). Wallpaper pattern alignment along garment seams. [TOG]. *ACM Transactions on Graphics*, *38*(4), 1–12. 10.1145/3306346.3322991

Yan, H., Zhang, H., Liu, L., Zhou, D., Xu, X., Zhang, Z., & Yan, S. (2022). Toward intelligent design: An AI-based fashion designer using generative adversarial networks aided by sketch and rendering generators. *IEEE Transactions on Multimedia*.

Yuan, M., Khan, I. R., Farbiz, F., Yao, S., Niswar, A., & Foo, M. H. (2013). A mixed reality virtual clothes try-on system. *IEEE Transactions on Multimedia*, *15*(8), 1958–1968. 10.1109/TMM.2013.2280560

Zhang, T., Wang, W. Y. C., Cao, L., & Wang, Y. (2019). The role of virtual try-on technology in online purchase decision from consumers' aspect. *Internet Research*, *29*(3), 529–551. 10.1108/IntR-12-2017-0540

Zhao, L., Liu, S., & Zhao, X. (2021). Big data and digital design models for fashion design. *Journal of Engineered Fibers and Fabrics*, *16*, 15589250211019023. 10.1177/15589250211019023

Zhu, X. J., Lu, H., & Rätsch, M. (2018). An interactive clothing design and personalized virtual display system. *Multimedia Tools and Applications*, *77*(20), 27163–27179. 10.1007/s11042-018-5912-x

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