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Prediction of Bust and Waist Size Based on Two-dimensional Images*

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Abstract

Human body measurement based on two-dimensional images has been widely applied in the clothing industry due to its cost and operational advantages. However, the current accuracy of human body circumference measurement is low. This article aims to propose a high-precision method for measuring human body circumference, taking bust circumference and waist circumference as examples, and based on 120 virtual simulations of human bodies, proposes a method to extract human body bust circumference size from front and side angles images. Using the feature value pixel size to calculate the trapezoid perimeter and the ellipse perimeter, and comparing them with the difference of bust circumference and waist circumference sizes, machine learning is applied to build a size prediction model, thus obtaining the values of bust circumference and waist circumference. The experimental results show that the average prediction errors of bust girth and waist girth by the proposed method are 0.26 cm and 0.24 cm, respectively, indicating good prediction performance and applicability for practical production. The proposed method effectively reduces the measurement errors of girth dimensions in image measurement and provides methods and ideas for non-contact human body measurement research.

Keywords: Anthropometric dimension; Girth measurement; Neural network; Linear regression

1 Introduction

The human body shape is the basis of garment structural design [1]. Human body size is the basis for judging body shape. The application of human body measurements in the clothing field is extensive, such as clothing structure design, customisation, virtual online fitting, personalised virtual character production, etc. Human body size measurement includes two methods: contact measurement and non-contact measurement. Technological advances have made non-contact

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measurement popular due to its speed, accuracy, comprehensiveness and efficiency [2]. At present, non-contact measurement methods include three-dimensional scanning and two-dimensional imaging. Three-dimensional scanning relies on large-scale scanning equipment, has a high cost, and is limited by environmental and spatial factors. It is not easy to move [3] making it difficult for large-scale promotion and use. The two-dimensional imaging method involves taking several images of the human body from the front, side and other directions. Body measurements are obtained through three key technologies: contour extraction, feature point detection and size estimation [4]. This method has low equipment requirements, is simple to operate, and is low-priced. For some lightweight enterprises and online shopping consumers, using the two-dimensional image method to obtain human body size data is convenient, fast, and effective.

Deng et al. [5] use the image difference method to separate the subject from the background regarding contour extraction and feature point detection. The image was then binarised and denoised to obtain the human contour. Feature points were defined and extracted using a human proportion method. This method can obtain a limited number of points, and the fixed proportion method does not take into account the differentiated characteristics of human body structure; Hu et al. [6] use colour separation and Sobel operator edge detection to obtain the human contour and ABSS (Adaptive Body Structure Segmentation) algorithm for human body structure segmentation; Jiang et al.[7] used the Canny edge detection method to obtain the human contour and performed custom encoding using the Freeman8 encoding method. Both studies [6, 7] used local edge curvature methods to extract feature points. However, this method cannot eliminate the interference of clothing, and some special body shapes cannot be accurately extracted. The practical application is limited.

In measuring human body size, length and width can be obtained directly from the pixel distance between photo feature points. Therefore, the research difficulty and focus are concentrated on measuring circumference size. At present, the primary methods for measuring circumference include linear regression [8, 9], elliptical fitting [10], and neural networks [11, 12]. The circumference measurement method based on linear regression needs to collect a large amount of human body data to fit the circumference calculation equation. The speed is fast, but the circumference of the human body will be affected by many other size parameters of the human body. Therefore, it isn't easy to define the circumference mathematically with a unified equation. Different body types greatly affect the circumference measurement method based on elliptical fitting and have a poor measurement effect for some special body types. The circumference measurement method based on a neural network uses two-dimensional image feature data for machine learning to predict circumference size. However, this method is affected by the sample data, which leads to large measurement errors in human body size.

In summary, there are still many problems with the measurement of human body dimensions using two-dimensional images, mainly reflected in the following aspects:

- The contour extraction method is limited, mainly affected by lighting and the clothing worn by the subject.
- Most feature point detection is based on the human body contour for feature point positioning. Due to the error of contour extraction, the feature point positioning is inaccurate, which affects the measurement of human body dimensions.
- The measurements of human body dimensions in width and length are relatively accurate. However, the measurement error is large in circumference measurement, especially in im-

portant human body dimensions such as bust circumference, waist circumference, and hip circumference.

Human body dimension measurement accuracy is closely related to contour extraction, feature point detection, and algorithms. To solve the problem of large measurement errors in girth measurement based on two-dimensional image measurement methods, we propose a method to predict bust size based on ellipse circumference and trapezoid circumference, taking bust size as an example. We conducted experimental verification with 120 virtual human bodies as samples.

2 Methodology

2.1 Generation of Virtual Human Body Samples

2.1.1 Virtual Human Body and Real Human Body

For machine learning-based two-dimensional image human body measurement, it is necessary to establish a body shape database containing various body shapes as training data. Therefore, the data quality largely determines the model's accuracy for body shape recognition. Traditional body shape recognition researchers usually use real human bodies, but they have some disadvantages as experimental samples:

- The collection object is limited. Real anthropometry needs to be carried out offline, and space is limited. The experimenter is required to wear only underwear during the experiment, which involves personal privacy, making it difficult to recruit experimental subjects.
- The measurement steps are tedious. Offline measurement requires the measurer and the experimenter to measure one-on-one, which requires time arrangement for the experiment participants and repeated measurement of the experimenter to reduce the operation error, consuming a lot of time.
- The measurement error is uncontrollable. Manual measurement is greatly affected by the measurement method of the operator, and it cannot guarantee that the standard of each measurement is consistent, which will inevitably cause errors in the measurement data.

Virtual human bodies integrate disciplines such as computer vision, computer graphics, and ergonomics. They use computers to simulate real human bodies and present them in a three-dimensional form. Virtual human bodies are not limited by time and space, measurement standards are easy to standardise, and the cost is low. Nowadays, the application of the virtual human body in garment digitisation is very common, and there are already many applications in the research of garment structure [13]. Based on this, we propose using virtual human bodies for experiments.

2.1.2 Generation of Virtual Human Body

We used the definition of the body type of young women in the eastern region of China according to the literature [14]. We used the virtual human bodies preset by Style3D software to prepare our experimental samples. It can adjust the human body according to body size data. We obtained 120 simulated digital virtual human bodies of Chinese women with heights ranging from 158 cm to 170 cm as experimental subjects. The model maintains an A-pose posture: arms straight with an angle of about 30° between the arms and the torso, and feet slightly narrower than the shoulder width [8]. Images of the model from two angles, front and side, were collected using a virtual camera. The image resolution is 300dpi, and the image size is 1 080 px (width) × 1 500 px (height).

2.1.3 Extraction of Two-dimensional Feature Points

This article focuses on measuring girth dimensions, so it does not do much research on the feature point extraction method. We adopt the method of manually calibrating feature points. A total of 41 FPs are marked, and 26 width dimensions and 10 height dimensions are extracted from them (refer to Fig. 1). The definitions of the feature dimensions are shown in Table 1.

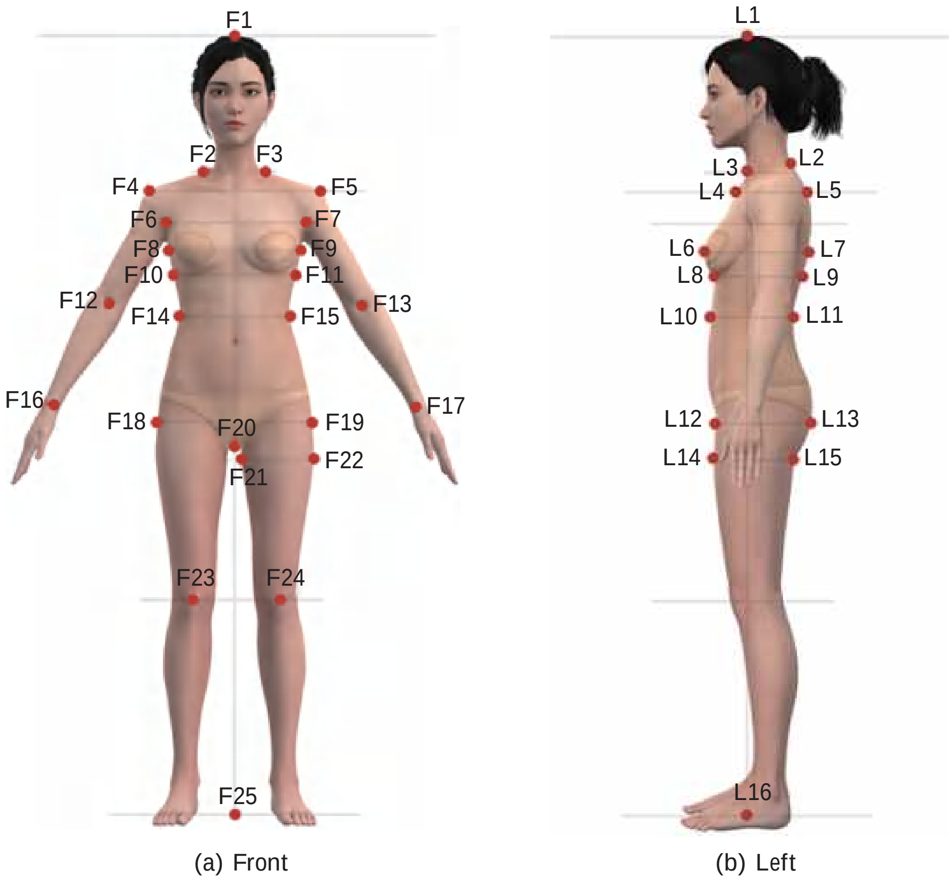

Fig. 1: FPs marked on the front view and left view

2.1.4 Data Preprocessing

Data errors may be caused by personnel negligence during the data collation stage. To address this, we performed singular value detection on the data to screen, verify, and correct any incorrect data. After this process, we still retained 120 sample sizes. Additionally, we have normalised the data to eliminate the impact of different feature scales.

Table 1: The two-dimensional feature dimension definition

Dimension code	FPs	Dimension code	FPs
Width		W19	L3, L2
W1	F4, F5	W20	L14, L15
W2	F4, F2	W21	L6, L10
W3	F8, F9	W22	L7, L11
W4	F10, F11	W23	L6, L8
W5	F14, F15	W24	L7, L9
W6	F18, F19	W25	L10, L12
W7	F2, F3	W26	L11, L13
W8	F6, F7	Height	
W9	F4, F12	H1	F1, F25
W10	F12, F16	H2	F4, F2
W11	F21, F22	H3	F4, F12
W12	F8, F14	H4	F12, F16
W13	F8, F10	H5	F20, F25
W14	F14, F18	H6	F14, F20
W15	L6, L7	H7	F22, F24
W16	L8, L9	H8	F24, F25
W17	L10, L11	H9	L2, L5
W18	L12, L13	H10	L2, L3

2.2 Design of the Bust Size Prediction Model

The bust curve of a woman can be approximated as a square shape with four sides approximately straight and rounded corners at the turning points (refer to Fig. 2(a)). We can approximate the bust curve as an isosceles trapezoid with a longer upper base and a shorter lower base (refer to Fig. 2(a)-(b)). Therefore, we can use the trapezoid calculation formula to solve the bust size measurement problem. The calculation formula of the isosceles trapezoid is shown in Eq. (1).

$$L_2 = n_1 + n_2 + 2\sqrt{m^2 + \frac{(n_1 - n_2)^2}{4}} \tag{1}$$

In Eq. (2), n_1 and n_2 represent the lengths of the trapezoid's two bases, and m represents its height.

Let the bust width be W; the bust thickness be T, the breast spread be P, and the difference between the trapezoidal circumference and the bust size be σ. Then, the calculation formula for bust size can be represented by Eq. (2), respectively.

$$L_{\text{Bust\_trapezoid}} = W + P + 2\sqrt{T^2 + \frac{(W - P)^2}{4} + \sigma} \tag{2}$$

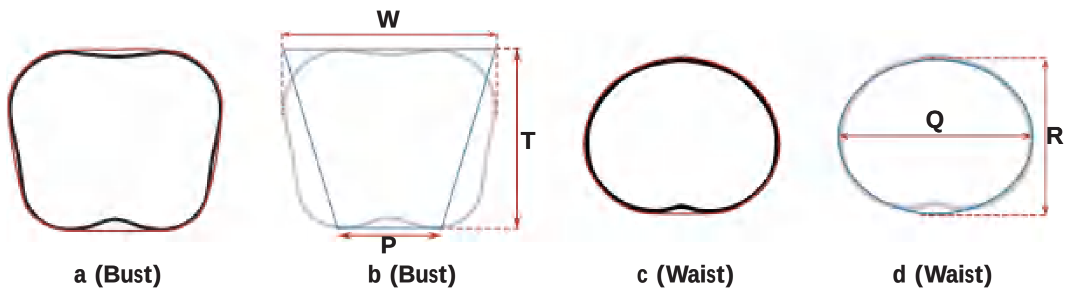

Fig. 2: Trapezoidal fitting of bust and elliptical fitting of waist

In the same way, the female waist circumference is approximately an ellipse shape [10, 15-17] (refer with: Fig. 2(d)).

Let the waist width be Q, the waist thickness be R, the difference between the trapezoidal circumference and the waist size be ϕ. Then the calculation formula for waist size can be represented by Eq. (3), respectively.

$$L_{\text{waist\_ellipse}} = \pi \left[\frac{3}{4}(Q + R) - \frac{\sqrt{QR}}{2} + \varphi \right] \tag{3}$$

Using the image information, we can obtain the pixel distance of the feature values. Using the known ratio of the actual height to the pixel height, we can calculate the actual width or actual height of each feature value. Let the actual height be H, the pixel height be h, and the pixel size of the feature value to be calculated be x. The expression formula for the actual size Y of each feature value is shown in Eq. (4).

$$Y = Hx/h \tag{4}$$

We use the 36 feature values obtained from the two-dimensional image as the input and P, σ and ϕ as the output to build a machine learning model. We randomly divide the samples into two parts: the training set and the test set. The training set is used for model training, and the test set is used to validate and adjust the model effect after training. Fig. 3 shows the specific process of bust and waist size prediction.

3 Experimental Results and Data Analysis

3.1 Prediction Result Analysis

Using SPSS software to build MLP neural network prediction models for P, σ and ϕ respectively, setting the number of hidden layers to one, the number of hidden units to four, the function to hyperbolic tangent, and the scaled conjugate gradient as the optimization algorithm. We use the mean absolute error (MAE) and R^2 to evaluate the prediction results of the model. The MAE value can better reflect the actual situation of the prediction value error, and the closer its value is to 0, the better the model prediction effect; R^2 can reflect the correlation degree between the prediction value and the true value, and the closer its value is to 1, the better the model prediction effect. The prediction results of P, σ and ϕ are shown in Table 2.

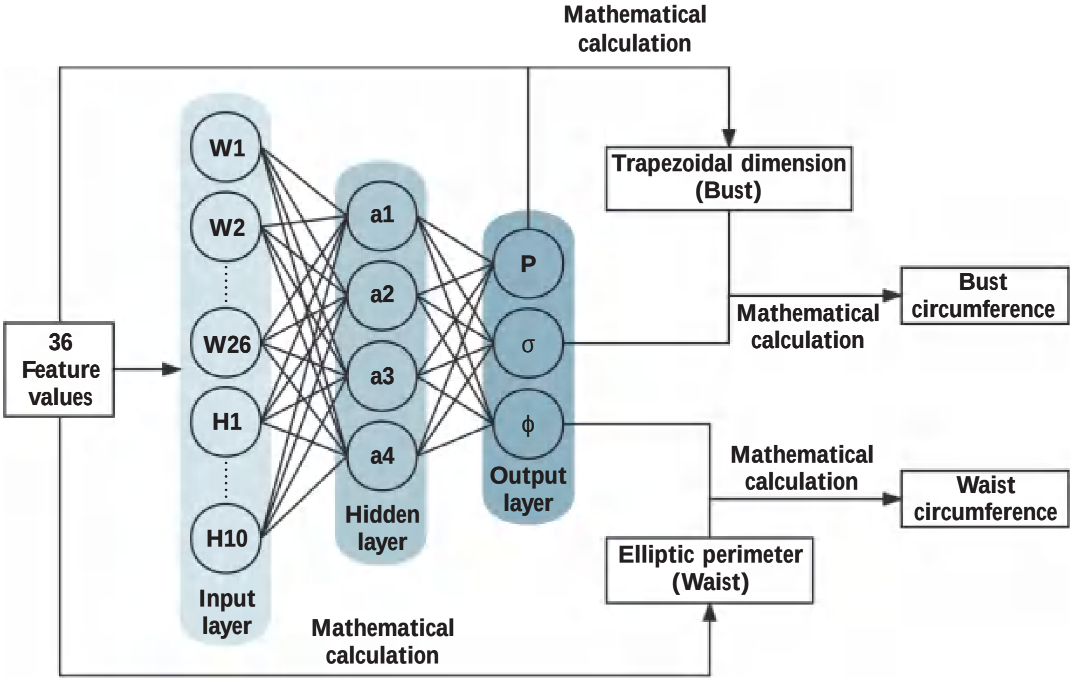

Fig. 3: Bust size and waist size prediction flowchart

Table 2: The prediction results of the three parameters

	R^2	MAE (cm)	Max (cm)	Min (cm)	E≤1 cm (%)	1 < E ≤2 cm (%)	E > 2 cm (%)
σ (Bust parameter)	0.630	0.2	0.77	0	100	0	0
ϕ (Waist parameter)	0.633	0.24	1.39	0	99	1	0
P (Breastspread)	0.988	0.09	0.44	0	100	0	0

As can be seen from the table, the prediction errors of the three parameters P, σ and ϕ are all within 2 cm, and 99% of the prediction errors are within 1 cm. Among them, the prediction effect of the breast distance is the best, with the MEA value within 0.1 and R^2 reaching 0.988, which indicates that the predicted breast distance value can accurately express the numerical value of the real breast distance. Since the final prediction result of the bust is jointly determined by the breast distance P and the parameter σ, it is necessary to perform mathematical calculations on the predicted results to obtain the prediction results of the bust and waist. The results are shown in Table 3.

Table 3: Bust and waist prediction results

	R^2	MAE (cm)	Max (cm)	Min (cm)	E ≤1 cm (%)	1<E≤2 cm (%)	E>2 cm (%)
Bust	0.997	0.26	1.05	0	99	1	0
Waist	0.998	0.24	1.39	0	99	1	0

As can be seen from the table, by substituting the three parameters P σ and ϕ into the mathematical calculation formulas of the bust and waist, the prediction errors of the bust and waist are both within 2 cm, the MEA are both less than 0.3, and the R^2 are both greater than

0.8. Thus, the prediction results can better reflect the real bust and waist, and the prediction effect of the waist is slightly better than that of the bust.

3.2 Comparative Analysis with other Models

In this paper, we compare the prediction method of bust size and waist size with the current mainstream size prediction methods, such as linear regression and MLP neural network training, using MEA, R^2, and the error curves of each model prediction result as the measurement criteria. Fig. 4 shows the comparison of the MAE values and R^2 values of each model prediction, and Fig. 5 shows the comparison of the errors of each model prediction.

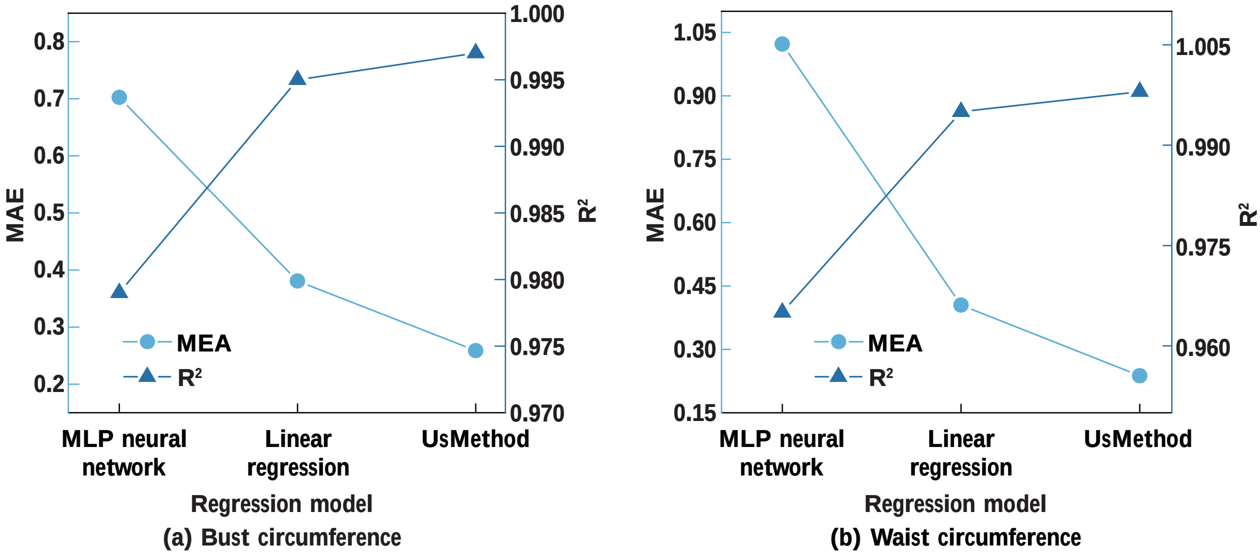

Fig. 4: Comparison of MAE and R^2 of each model

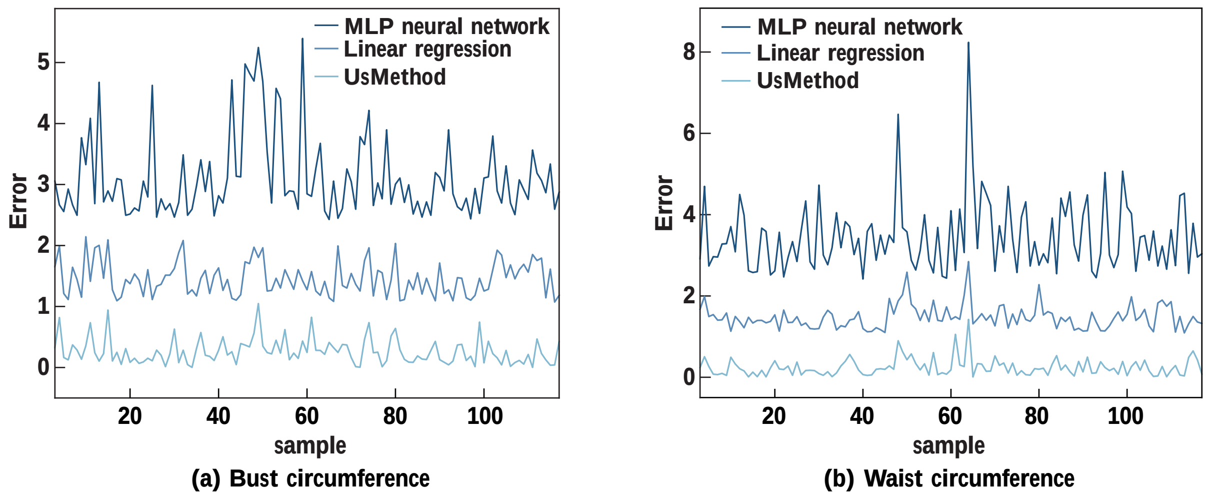

Fig. 5: Comparison of prediction errors of each model

According to Fig. 4, it can be seen that, whether it is the prediction of bust or waist, the MEA value of our method is the smallest, followed by Linear Regression, and MLP neural network is the largest; on the R^2 value, our method is the largest, followed by linear regression, and MLP neural network is the smallest. This indicates that our model can fit enough information, and the fitting effect is the best.

According to Fig. 5, it can be seen that the error value fluctuation range of our method for bust and waist size prediction is relatively narrow, which proves that for the same set of data, the error value predicted by our method is the smallest. In contrast, the MLP neural network model has the largest error of up to about 5 cm, which is unacceptable in garment pattern making, and may lead to the garment made with this data not conforming to the human body shape. Compared with that, our model has the best prediction effect on bust and waist size.

4 Discussion

Regarding measuring human body dimensions using two-dimensional images, most previous studies only used neural networks and linear regression methods [6, 11]. These methods have significant errors in the measurement of human body circumference dimensions. In this study, we combined mathematical methods with neural networks. Compared with previous methods, our method shows more satisfactory results in the accuracy of measuring human body circumference dimensions. This has further promoted the practical application of image body measurement in the market.

5 Conclusion

We propose a method for measuring women's bust and waist sizes based on two-dimensional images. To avoid the error caused by automatic feature point detection accuracy, we manually label 41 feature points from the front and side images. We extract 26 feature values from the width dimension and 10 feature values from the height dimension according to the human body measurement method. We propose a different method for the bust and the waist to measure the circumference size.

We use a trapezoidal fitting method for the bust, which approximates the bust as an isosceles trapezoid and performs mathematical calculations. We use an elliptical fitting method for the waist, which treats the waist as an ellipse and performs mathematical calculations. We extract three unknown parameters, construct a neural network model to predict them, and finally obtain the bust and waist values by mathematical calculations. The experimental results show that this method's average error of the bust prediction is 0.26 cm, and the average error of the waist prediction is 0.24 cm. The measured errors are all less than 2 cm, within the allowable range of clothing size errors. The prediction effect is good, and the experimental results are better than the current mainstream measurement methods.

This method can obtain accurate bust and waist sizes by taking only two photos of the human body, which improves the problem of inaccurate measurement of the circumference size by non-contact measurement in traditional methods. It has some reference value for online clothing customization, virtual fitting and other applications. Due to the focus of this paper, the problem of feature point recognition and calibration is avoided, but this is still a key problem of non-contact human body size measurement. Therefore, relevant research can be added to improve the measurement process in the follow-up research.

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