Non-contact clothing anthropometry based on two-dimensional image contour detection and feature point recognition

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ABSTRACT – REZUMAT

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Developing the technology of estimating human body size from two-dimensional images is the key to realising more digitalization and artificial intelligence in the textile and garment industry. Therefore, this paper is an in-depth study of estimating body sizes from two-dimensional images in a self-collected database of human body samples. First, the artificial thresholds in the Canny edge operator were replaced by adaptive thresholds. The improved Canny edge operator was combined with mathematical morphology so that it could detect a clear and complete single human contour. Then a joint point detection algorithm based on a convolution neural network and human proportion is proposed. It can detect human feature points with different body proportions. Finally, front and side images and manual body measurements of 122 males aged 18–22 years were collected as the human sample database, calculating the length and fit of the girth size. Compared with manual body measurement data, the error of human length and girth size parameters within the national standard range of –1.5 ~ 1.5 cm can reach 91% on average. This study provides an accurate and convenient anthropometric method for digital garment engineering, which can be used for online shopping and garment customization, and has a certain practical value.

Keywords: *anthropometry, textile clothing, image processing, contour detection, feature point detection*

Antropometrie fără contact bazată pe detectarea conturului imaginii bidimensionale și recunoașterea punctelor caracteristice

Dezvoltarea tehnologiei de estimare a dimensiunii corpului uman din imagini bidimensionale este cheia pentru a facilita digitalizarea și inteligența artificială în industria textilă și de îmbrăcăminte. Prin urmare, această lucrare este un studiu aprofundat al estimării dimensiunilor corpului din imagini bidimensionale, într-o bază de date auto-colectată de eșantioane ale corpului uman. În primul rând, pragurile artificiale din operatorul de margine Canny au fost înlocuite cu praguri adaptative. Operatorul de margine Canny îmbunătățit a fost combinat cu morfologia matematică, astfel încât să poată detecta un singur contur uman clar și complet. Apoi, este propus un algoritm de detectare a punctului comun bazat pe rețeaua neuronală convoluțională și proporția umană. Se pot detecta punctele caracteristice umane cu diferite proporții ale corpului. În cele din urmă, imaginile frontale și laterale și dimensiunile corporale preluate manual ale unui număr de 122 de bărbați cu vârsta cuprinsă între 18 și 22 de ani au fost colectate ca bază de date pentru eșantioane umane, calculându-se lungimea și circumferința. În comparație cu datele antropometrice ale corpului preluate manual, eroarea parametrilor de lungime și circumferință a corpului uman în intervalul standard național de –1,5 ~ 1,5 cm poate ajunge la o medie de 91%. Acest studiu oferă o metodă antropometrică precisă și convenabilă pentru modelarea digitală a îmbrăcămintei, care poate fi utilizată pentru cumpărături online și personalizarea articolelor de îmbrăcăminte și are o anumită valoare practică.

Cuvinte-cheie*: antropometrie, îmbrăcăminte, procesarea imaginilor, detecția conturului, detecția punctului caracteristic*

INTRODUCTION

With the increasing popularization of digital and intelligent consumption patterns such as online clothes shopping and personalization, people have higher requirements for the style and fit of their clothing. Body size data have a decisive role in digital garment engineering. Therefore, it is necessary to conduct in-depth research to develop a fast and efficient anthropometric measurement method suitable for the garment industry.

Existing methods for measuring the human body include traditional manual measurement, non-contact measurement from three-dimensional data, and non-contact measurement from two-dimensional images [1, 2]. Manual measurement requires professional skills, whereas non-contact measurement from three-dimensional data requires the person to wear specific clothing. The equipment needed is large and expensive. Thus, these two methods are difficult for ordinary consumers and have low universality. In contrast, the non-contact measurement from two-dimensional images of the human body can obtain body parameters. Multiple photographs are taken from different angles by a user with a camera or mobile phone [3], which is convenient and quick to do. Two-dimensional anthropometry can be divided into three steps: contour detection, feature point detection, and girth fitting.

Several scholars have researched two-dimensional anthropometry. For example, Qin and Li [4] replaced the Gaussian filtering in the traditional Canny edge operator with median filtering. Xu [5] used the classical Canny edge operator and the Otsu algorithm to obtain human contours. Some scholars have applied traditional feature point detection algorithms, such as SURF and Harris, to human feature point detection [6, 7]. However, using a single algorithm is prone to the false detection of feature points. Zou et al. [8] defined the regions of feature points of each part according to the relative proportions of the human body. They calculated the maximum edge response points of each region and recorded them as feature points. However, this method relies too much on ergonomic proportions and has low positioning accuracy, so it is not suitable for people with atypical body proportions. Xia et al. [9] predicted the girth according to the shape of the characteristic section of the human body. Xing et al. [10] constructed a model for predicting human body dimensions using a multilayer perceptron neural network. The errors for these two methods were small, but three-dimensional scanning is still needed, and the process is cumbersome. Zhao et al. [11] constructed the three-dimensional human body in three different ways and then carried out anthropometry. The accuracy of the measurement results is high, but the main measurement size is the upper body size, which cannot provide a size reference for pants or skirts. In addition, the generation and processing of the three-dimensional human body require professionals to operate, and it takes 15 minutes to 1 hour, which is not suitable for the general public and takes a long time.

The above research indicates that the current methods for measuring the human body from two-dimensional images have problems, such as the need for complex calculations and limited applicability. The clothing industry urgently needs two-dimensional volume measurement technology that is simple to calculate, can be used by the public, and can be applied to different body proportions. Therefore, based on the improved Canny edge operator and mathematical morphology algorithm, this paper improves the robustness of detecting human contours from two-dimensional images. The resulting two-dimensional contours are clear and accurate. Then a method based on a convolution neural network for human joint point recognition and human proportion is proposed to complete feature point detection on contour image. This method can be applied to atypical body proportions and has strong universality. Finally, a self-collected human body database was established, which contains front and side photographs and manual measurements of 122 men aged 18–22. The data were used to estimate the length and girth parameters of the human body. A predictive girth regression model was creatively established based on width, thickness, and weight. The errors for the predicted length and girth parameters within –1.5 cm ~ 1.5 cm reached 91% on average. The method overcomes the problems of large size errors and low measurement efficiency. The estimated values agree well with the specifics of each individual, making it suitable for online clothes shopping and personalization.

FEATURE POINT RECOGNITION FROM TWO-DIMENSIONAL CONTOUR IMAGES

The key to obtaining accurate dimensions of the human body is correctly identifying the feature points of various parts of the body. These feature points must be detected from a single clear contour. Therefore, this section accurately identifies feature points based on two-dimensional contours, which lays the foundation for the subsequent calculation of length and girth parameters.

Human body image acquisition

To ensure the accuracy of dimensional data measurement, some requirements are put forward for users to take front and side photos. The specific requirements are as follows:

The shooting background should be as simple as possible, the light should be uniform, and there should be no serious reflection. Users try to wear more close-fitting, which can be clearly distinguished from the background colour.

Requirements for photographing posture: when taking frontal photos, stand upright with your arms open, and your legs and feet standing apart. When taking side photos, keep your body upright and your arms drooping naturally, but avoid covering the outer contour of your waist and hips, and stand with your legs and feet together. The shooting angle is required to be horizontal with the subject as far as possible to avoid problems such as portrait tilt and deformation.

Canny edge detection and mathematical morphology processing

Common operators for detecting the contours of a human body include the Laplacian operator, Sobel operator, Roberts operator, and Canny detection operator. In comparative analysis through the OpenCV module of Python, The Canny operator that can detect the real weak edge in the image and locate accurately is selected for contour detection, but the Canny edge operator will be affected by noise. and the edge of the object contour is generally determined by manually setting a double threshold [12], It is difficult to accurately grasp the size of the threshold. Therefore, an adaptive threshold is proposed to replace the traditional manually set threshold to avoid the uncertainty and complexity of manually setting the threshold. Then Canny edge operator is combined with mathematical morphology to reduce the impact of noise. The specific algorithm steps are as follows:

1. Greying RGB images.
2. Gaussian filter is used to smooth the image to remove high-frequency noise.
3. Calculate gradient amplitude and direction.
4. The gradient amplitude is suppressed by the non-maximum value.
5. At this time, an image with many discrete edge points is obtained, and then an adaptive threshold method is proposed to automatically detect and connect the real edge points. The high and low thresholds are constructed from the median of the pixel intensity for a single image channel [13]. First, we calculate the median pixel intensity in the image:

$$m = np.median(image) \tag{1}$$

Then, we use the median to calculate the high and low thresholds:

$$TH = \text{int}(\min(0, (1.0 + sigma) * m)) \tag{2}$$

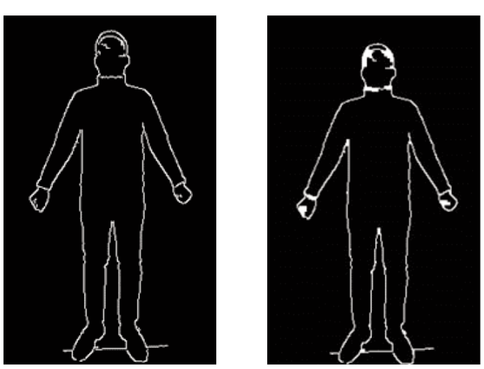
$$TL = \text{int}(\max(0, (1.0 - sigma) * m)) \tag{3}$$

where TH is the high threshold and TH – the low threshold. The function int ensures that the thresholds are integers. Here, $sigma$ = 0.33 is a fixed parameter [14]. The high and low thresholds are used in Canny edge detection, as shown in figure 1, *a*.

It can be seen from the figure that the improved Canny algorithm with adaptive thresholds can identify the real edge, but the head and other parts are still prone to stray edges. To obtain a single and complete human lateral contour, a method combining the Canny edge operator and mathematical morphology is proposed. To remove stray edges and noise, the closed operation method of expansion first and corrosion is adapted to process the image further. The results after this morphological processing are shown in figure 1, *b*.

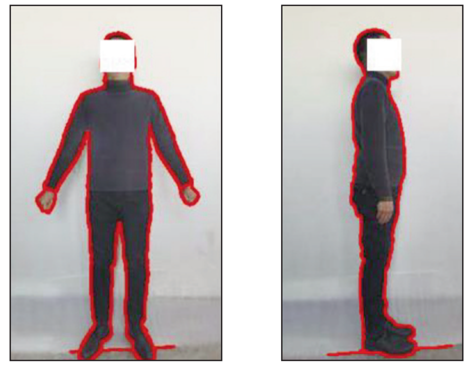
OpenCV module in Python is used to automatically detect the outer contour of the image after morphological processing, and the detected contour is displayed in the original image. The detection results are shown in figure 2.

It can be seen that for a subject standing against a relatively simple background and wearing their well-fitting clothes, the outline of their body was clearly



a ***b***

Fig. 1. Edge detection results: *a* – adaptive thresholds; *b* – morphological processing



a ***b***

Fig. 2. Detected front and side contours of a person: *a* – front red outer contour; *b* – side red outer contour

and completely recognized. After the closed operation, the contour is consistent with the original human image. Thus, automatic recognition can be realized without manual intervention, which is conducive to improving the efficiency of image detection while protecting the user's privacy to a certain extent.

Feature point detection based on convolution neural network and human proportion

Body length and girth parameters can be estimated accurately only if the feature points are correctly located and detected. To solve the problems of wrong detections, missing detections, and inaccurate positioning prevalent in current methods for feature point detection, a feature point detection method based on convolutional neural network VSSC (via soft gated skip connections) [15] human joint point recognition algorithm and human proportion is proposed.

Feature point detection based on MPII data set [16]. Python is used to test the joint points of a two-dimensional human image, in which the front image includes 12 points, and the side image includes 7 points on the right side of the human body. The experimental results after automatically marking the coordinate position of joint points are shown in the red dot in figure 4.

It can be seen from figure 4 that the joint point recognition algorithm can accurately locate the head, shoulder, arm, and knee, but cannot detect the chest, waist, or sole points, but these three parts are key for the human body measurements. Therefore, in this paper, we calculate the positions of these three parts using the relative proportions of a human body as used in engineering applications [17, 18]. That is, the chest coordinates (C_x,C_y) are calculated according to the relationship between the neck and the chest:

$$C_x = N_x \tag{4}$$

$$C_y = N_y + (Lf_y - top_y) * 0.15 \tag{5}$$

where: N_x is the abscissa of the neck, N_y – the ordinate of the neck, Lf_y – the ordinate of the bottom of the left foot, and top_y – the ordinate of the top of the head.

Calculate the characteristic points of the waist (W_x, W_y) according to the relationship between the waist and the hips:

$$W_x = (Lh_x - Rh_x)/2 + Rh_x \quad (6)$$

$$W_y = Lh_y - (Lf_y - top_y) * 0.105 \quad (7)$$

where: Lh_x is the abscissa of the left hip and Rh_x – the abscissa of the right hip, Lh_y – the ordinate of the left hip.

The coordinates of the sole points are (F_x, F_y). They were calculated from the coordinates of the ankle point:

$$F_x = Ra_x \quad (8)$$

$$F_y = 0.066 (Ra_y - top_y) / 0.934 + Ra_y \quad (9)$$

where: Ra_x is the abscissa of the right ankle and Ra_y – the ordinate of the right ankle. The left ankle point can be obtained in the same way.

The resulting joint points are shown in figure 3. The chest, waist, and sole points are marked with green points.

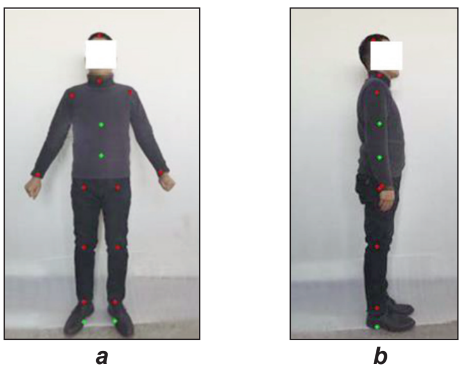


Fig. 3. Detected complete feature points: *a* – front joint points; *b* – side joint points

Using the joint point coordinates shown in figure 3, the feature points were detected for the red contour image in figure 2. The obtained positions of the feature points are shown in figure 4. Those at the front and side are represented by P and S, respectively.

From the feature point detection results, it can be seen that the feature point detection method based on the combination of convolution neural network and human proportion proposed in this paper can accurately detect the feature points of the top of the head, shoulders, chest and waist, and the positions of the detected feature points of each part are consistent with the feature positions defined in the

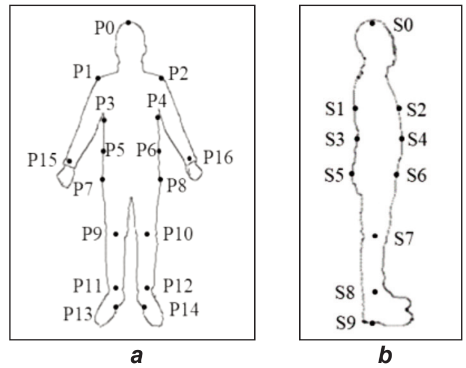


Fig. 4. Location of feature points: *a* – front joint points; *b* – side joint points

national standard. The positioning is accurate and the calculation is simple, which is suitable for groups with different body proportions.

CALCULATION OF HUMAN BODY LENGTH AND GIRTH PARAMETERS

According to the key dimensions and actual needs of taking anthropometry, 122 male images aged 18–22 were collected by mobile phones and used a soft ruler and other tools to measure the body manually. The numbers of pixels for 10 parameters (height, arm length, shoulder width, chest width, chest thickness, waist width, waist thickness, hip width, hip thickness, and pants length) were obtained from the collected images. The above dimensions and the actual dimensions of the chest girth, waist girth, and hip girth were measured manually. The weight of each participant was recorded by a standard electronic scale. It is used to predict the length and circumference of the human body.

Calculation of lengths

The height measured manually for the subject is H, whereas the pixel value of the height in the image is based on the y-coordinates of two feature points. Thus, the pixel height of the front image is P_0P_{13}, and the pixel height of the side image is S_0S_9 (figure 4). Then, the ratios of the real height and the pixel heights in the front side images are Pr and Sr, respectively:

$$Pr = H/P_0P_{13} \quad (10)$$

$$Sr = H/S_0S_9 \quad (11)$$

The physical sizes of the other lengths were calculated by scaling. The formulas are listed in table 1.

Table 1

FORMULAS FOR THE IMAGE SIZE OF EACH PART			
Position	**Formula**	**Position**	**Formula**
Shoulder width P_{sw}	$P_{sw} = Pr\ P_1P_2$	Waist width P_{WW}	$P_{WW} = Pr\ P_5P_6$
Arm length P_L	$P_L = Pr\ P_1P_{15}$	Waist thickness S_{WT}	$S_{WT} = Sr\ S_3S_4$
Trouser length S_L	$S_L = Sr\ S_3S_9$	Hip width P_{HW}	$P_{HW} = Pr\ P_7P_8$
Chest width P_{CW}	$P_{CW} = Pr\ P_3P_4$	Hip thickness S_{HT}	$S_{HT} = Sr\ S_5S_6$
Chest thickness S_{CT}	$S_{CT} = Sr\ S_1S_2$	-	-

Calculation of body girths

In this section, a regression model is established. Altogether, 100 samples were randomly selected from the database and used to build the model, and 22 samples were used to verify the model.

Correlation analysis

For the 100 men, the Pearson correlation coefficient was used to analyse the linear relations between the actual chest, waist, and hip girths (dependent variables) and the real weight and the real width and thickness of the corresponding body part (independent variables) [19]. The results are listed in table 2.

Table 2

CORRELATION COEFFICIENT BETWEEN EACH FACTOR AND EACH GIRTH			
Position	**Weight**	**Width**	**Thickness**
Chest girth	0.8727	0.7861	0.7513
Waist girth	0.7943	0.8012	0.8242
Hip girth	0.9122	0.79283	0.7897

It is generally considered that there is a correlation when the correlation coefficient is greater than 0.6. It can be seen from the table that the correlation coefficient between each girth and the weight, width, and thickness is greater than 0.6, indicating that these three factors can be used to establish a regression model with the girths.

Shape classification and model establishment

To improve the accuracy of size prediction, the section shapes of the chest, waist and hip are divided into a short circle, circular length and flat length according to the width thickness relationship. The ratio of the section shape is closer to the median value of the class, the stronger the linear relations are between the width and thickness and the girth, so the better the fitting degree of the prediction model. Therefore, the samples were divided into three classes using the width-to-thickness ratio *r*, as listed in table 3.

Establish regression model for each category:

$$W = a_0 + a_1Z + a_2K + a_3T \tag{12}$$

where: Z is the weight, K – the width, and T – the thickness.

According to the classification, the multiple linear regression method is used to fit the regression model for each category of the three parts, and the judgment coefficient R^2 and adjustment R^2 of the regression model are listed in table 4.

It can be seen from the table that the adjusted R^2 of the regression model after classification has been improved, basically above 0.9, indicating that at least 90% of the effective information of the sample value is used to explain the regression equation, and the model fitting effect is good. Among them, the fitting degree improvement rate of the chest and hip is lower than that of the waist, mainly because the waist section shape itself has a large difference, and the characteristics of each category after classification are more significant and more relevant, so the fitting degree improvement rate is higher, while the cross-section shape difference of chest and waist is relatively small, and the fitting degree improvement rate

Table 3

SHAPE CLASSIFICATION						
Position	**Class A**		**Class B**		**Class C**	
	Number	Range	Number	Range	Number	Range
Chest	23	r < 1.40	53	1.40 ≤ r ≤ 1.55	23	r > 1.55
Waist	22	r < 1.35	43	1.35 ≤ r ≤ 1.45	35	r > 1.45
Hip	30	r < 1.40	51	1.40 ≤ r ≤ 1.50	17	r > 1.50

Table 4

REGRESSION EQUATIONS ESTABLISHED AFTER SHAPE CLASSIFICATION					
Position	**Class**	**Regression equations**	**R^2 before**	**R^2 after**	**Promotion (%)**
Chest	A	$W_{CA} = 1.9688 + 0.2798Z + 1.5161K + 0.9634T$	0.8571	0.9072	5.8
	B	$W_{CB} = 4.8169 + 0.2468Z + 1.4023K + 1.1134T$		0.9346	9.0
	C	$W_{CC} = 7.3438 + 0.2644Z + 1.0066K + 1.5727T$		0.9778	14.1
Waist	A	$W_{YA} = 2.5612 + 0.0920Z + 1.5554K + 1.4213T$	0.8284	0.9583	15.7
	B	$W_{YB} = 0.0789 + 0.1192Z + 1.7014K + 1.2349T$		0.9767	17.9
	C	$W_{YC} = 2.3875 + 0.0945Z + 2.1957K + 0.3998T$		0.9514	14.8
Hip	A	$W_{HA} = 31.8552 + 0.3339Z + 1.1864K + 0.0614T$	0.8553	0.9290	8.6
	B	$W_{HB} = 15.3843 + 0.3207Z + 2.5362K – 1.1982T$		0.9503	11.1
	C	$W_{HC} = 49.7284 + 0.3781Z + 0.9081K – 0.5501T$		0.8594	0.5

Table 5

LENGTH ERROR DISTRIBUTION DIAGRAM				
Part of the body	**Min error**	**Max error**	**Mean value of error**	**Accuracy within ±1.5 cm (%)**
	(Image value – Manual value) (cm)			
Shoulder width	0.100	2.250	0.897	93.3
Arm length	0.060	1.968	0.869	91.1
Trouser length	–0.150	2.230	1.100	82.2

Table 6

GIRTH ERROR DISTRIBUTION DIAGRAM				
Part of the body	**Min error**	**Max error**	**Mean value of error**	**Accuracy within ±1.5 cm (%)**
	(Image value – Manual value) (cm)			
Chest girth	–0.025	1.618	0.056	90.9%
Waist girth	0.034	1.548	0.665	95.5%
Hip girth	0.008	–1.671	0.729	86.4%

is lower than that of the waist, but it is generally improved, which indicates that the prediction error value after classification has been improved.

VERIFICATION AND ANALYSIS

To evaluate the reliability of the model, the proposed anthropometric algorithm is applied to 22 samples randomly selected. The length and three girths of body parts were estimated and compared with manual measurement. The reasons for the accuracy and error of the estimation are analysed. First, the measurement results of shoulder width, arm length and trousers length are verified, and the results are shown in table 5.

Table 5 shows the error distributions and average errors for the shoulder width, arm length, and trouser length. The accuracies of the dimensions are listed in table 5. The errors for shoulder width are mostly distributed within ±1.5 cm. The average error for the shoulder width was 0.82 cm and for arm length, it was 0.92 cm, both of which are reasonable. The errors for trouser length were relatively larger. There was an average error of 1.12 cm and a large deviation, mainly because the pixel distance in the leg image was calculated from the waist point to the ankle point. Any bending of the leg or deviation in detecting the waist will have affected the estimated size of the trouser length. Most of the estimated trouser lengths were smaller than the real values.

Then, the predicted girth values of the chest, waist and hip are compared with the manually measured values, and the results are shown in table 6.

It can be seen from the table that the girth values of the chest, waist and hip predicted by the regression model established in this paper fit well with the manually measured dimensions, and the overall error range is basically within ± 1.5 cm. Among them, the error value of the waist is the smallest, and the fitting degree between the predicted value and the manual value is the best. After the complete statistics of length parameters and girth parameters, the obtained data meet the requirements of adult human body size error of –1.5 ~ 1.5 cm specified in GB/T1335.2-2008. National Garment Size [20].

CONCLUSIONS

This paper uses anthropometry based on two-dimensional images to extract human body measurements. Existing measurement methods with two-dimensional images often produce inaccurate positions for the feature points and are appropriate for only a limited range of body shapes. The proposed method was based on a self-collected human sample database. It combined the Canny edge detection operator with a mathematical morphology algorithm to recognize contours automatically. The contours were clear, complete, and consistent with the size of the original image. Joint point recognition and human body proportions were used to locate feature points accurately. The method is suitable for individuals with atypical body proportions. The number of samples with the average error of the final length and perimeter data within ±1.5 cm accounts for 91% of the total number of samples, which meets the size requirements of garment manufacturing. This approach can conveniently provide users with their body data for online shopping and personalized customization.

Although this method is better at extracting feature points and calculating girths than previous methods, it could be further improved. On the one hand, in terms of the establishment of the database, due to the limitations of the experimental environment and conditions, the amount of data collection is relatively small, and the age range involved is relatively concentrated. Therefore, when it is applied, it will have a better experience for 18–22 years old youth and people of similar ages, while it will have a relatively weak experience for other people with large age differences. With the continuous expansion of the subsequent database, The measurement accuracy based on the algorithm in this paper will continue to improve, and the age range involved will gradually expand and become more refined. On the other hand, we should do further research on the human body in a complex background to further improve the two-dimensional image anthropometry method proposed in this paper.

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