AdaBoost algorithm for the recognition of young women's body shapes based on 2D images

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ABSTRACT – REZUMAT

AdaBoost algorithm for the recognition of young women's body shapes based on 2D images

Classifying and recognizing the human body shape during human body measurements based on 2D images helps to improve measurement accuracy. In this paper, 430 young women's 2D body images were selected to establish 2D body datasets. The characteristic indices used to represent the body shape in 2D images were extracted by computer vision technology, namely the body height pixel value, projected unit area, and projected area ratio of the front and side of the body. The two-step cluster model was used to classify the body shape into three clusters: the tall, flat, and medium fatness type; the short, thin, and medium roundness type; and the round, fat, and medium height type. Then, the decision tree model and AdaBoost algorithm, an ensemble learning algorithm with the decision tree as the weak classifier, were used to recognize the body shape. The results show that the recognition accuracy of the decision tree recognition model was 93.19%. The body shape recognition method using AdaBoost achieved a better recognition effect than the decision tree model, and the recognition accuracy of the test set reached 97.35%. Through comparative study, we found that the recognition accuracy of the 2D body shape recognition method based on AdaBoost was improved and that the recognition accuracy was relatively stable. This study provides a new method for the recognition of human body shape in clothing customization and online shopping.

Keywords: *body shape classification, body shape recognition, 2D images, AdaBoost, decision tree*

Algoritmul AdaBoost pentru recunoașterea formelor corpului persoanelor tinere de sex feminin pe baza imaginilor 2D

Clasificarea și recunoașterea formei corpului uman în timpul măsurării acestuia pe baza imaginilor 2D ajută la îmbunătățirea preciziei măsurării. În această lucrare, au fost selectate 430 de imagini corporale 2D ale persoanelor tinere de sex feminin pentru a stabili seturi de date corporale 2D. Indicii caracteristici utilizați pentru a reprezenta forma corpului în imagini 2D au fost extrași prin tehnologia recunoaşterii vizuale computerizate, și anume valoarea pixelului înălțimii corpului, aria unității proiectate și raportul suprafeței proiectate a părții frontale și laterale a corpului. Modelul de tip cluster în doi pași a fost folosit pentru a clasifica forma corpului în trei clustere: tipul de înalt, plat și mediu de grăsime corporală; tipul scurt, subțire și mediu de rotunjime corporală; tipul rotund, gras și mediu de înălțime. Apoi, modelul arborelui decizional și algoritmul AdaBoost, un algoritm de învățare de ansamblu cu arborele decizional în calitate de clasificator slab, au fost utilizate pentru a recunoaște forma corpului. Rezultatele arată că precizia recunoașterii modelului arborelui decizional a fost de 93,19%. Metoda de recunoaștere a formei corpului folosind AdaBoost a obținut un efect de recunoaștere superior decât modelul arborelui decizional, iar precizia recunoașterii setului de testare a atins 97,35%. Prin studiu comparativ, s-a constatat că precizia metodei de recunoaștere a formei corpului 2D bazată pe AdaBoost a fost evident îmbunătățită și că precizia recunoașterii a fost relativ stabilă. Acest studiu oferă o nouă metodă de recunoaștere a formei corpului uman în personalizarea îmbrăcămintei și cumpărăturile online.

Cuvinte-cheie*: clasificarea formei corpului, recunoașterea formei corpului, imagini 2D, AdaBoost, arbore decizional*

INTRODUCTION

Intelligent customization of clothing has become indispensable in personalized clothing consumption at present. However, the realization of remote, fast, and accurate human body size acquisition has become the biggest bottleneck facing clothing enterprises during intelligent customization [1, 2]. The body shape affects the morphological features of the body. The rapid classification and recognition of the body shape can be applied to the anthropometry of clothing customization enterprises to improve measurement accuracy [3]. The existing classification standards of female body shape mainly include girth difference, cross-sectional shape, body surface angle, and characteristic index. According to the way of obtaining classified data, the body classification methods are divided into three categories: body shape classification based on 3D body scanning size, 3D–2D interactive body shape classification, and body shape classification based on 2D images. Wang et al. extracted data on 24 lower body parts with a 3D body scanner and divided the lower body into a tall and obese body type, a short and intermediate body type, and a tall and lean body type [4]. This is a body shape classification method based on 3D body size, which is mostly used in current body shape classification research [5]. With the development of 2D anthropometry research, multiple 3D–2D interactive body shape classification methods have been developed. Cai et al. proposed to use "3D scanning+photos" to classify and identify the waist–abdomen–hip figure of young women [6]. In this method, the body size from 3D scanning is used to classify the body shape, 2D body photo data are converted into a 3D body size, and then the body shape is identified. The method of body shape classification and recognition based on a 2D image refers to body shape classification by using the information features reflected by the 2D image, and it does not involve the 2D–3D transformation process. Based on the concept of 2D body type classification, Zhang et al. used the 3D point cloud data of young men to extract the 2D human angle. They selected the forward angle, back angle, shoulder oblique angle, neck-to-shoulder width ratio, and neck transverse sagittal diameter ratio to classify the neck and shoulder. Then, based on the front and side 2D photos of young men, the neck and shoulder shapes were automatically recognized [7], which simplified the process of the conversion of 2D data to a 3D size in literature [6]. At present, there are few studies on body type classification using 2D images exclusively, and mostly concentrated on the angle and some parts of the human body. The main reason is that 2D images reflect less human data information, which requires researchers to broaden the scope of classification feature selection.

The essence of human body shape recognition is the process of identifying the category to which body characteristic indices belong by using appropriate recognition rules based on body shape classification. The methods of recognition rules mainly include the interval method, the formula method, and methods based on artificial intelligence. The interval method involves dividing a certain feature of the body into several intervals, and the numerical value indicates the corresponding interval to which the body shape belongs. For example, the classification and discrimination method of body shape in the Chinese clothing size standard. The formula method is, to sum up multiple body shape characteristics into functional equations by statistical methods and then complete body shape recognition by bringing the characteristics of the unknown body shape into the formula during body shape recognition [8]. The body shape recognition method based on artificial intelligence has high accuracy and wide applicability, making it the most widely used method in research on body shape recognition at present. The two types of body shape recognition methods based on artificial intelligence are recognition algorithms based on an individual learner and recognition algorithms based on ensemble learning. Recognition algorithms based on individual learners mainly include decision trees, SVM, and naïve Bayes algorithm. Jing et al. used the naïve Bayes algorithm to differentiate the body shape of girls based on 27 measurement sizes [9]. In contrast, recognition algorithms based on ensemble learning mainly include the Boosting and Bagging algorithms [10]. XGBOOST is one Boosting learning algorithm [11]. Liu et al. used the back hip length-to-waist girth ratio and back hip length-to-hip girth ratio as clustering indexes, divided the hip shape of young women in Xinjiang into three types, and used Python software to establish a hip recognition model based on the XGBOOST algorithm to realize automatic body shape recognition [12]. Moreover, random forest [13] is a special Bagging algorithm. Yin et al. described and classified the female body shape from three aspects: whole body type, morphological characteristics, and torso silhouette. They used the random forest algorithm to identify the three types of characteristics [14].

Through much literary analysis, researchers have found that the previous body characteristic analyses and recognition methods are based on the obtained body size, but it is difficult to obtain 3D body sizes remotely during clothing customization. Therefore, in this paper, 2D body photos, which are the easiest to collect in garment remote customization, were used as the research object. First, the characteristic indices of the body were extracted based on computer vision technology, and the body shape was divided into three types by using the two-step cluster model. Then, the decision tree and AdaBoost models were used to recognize bodies in 2D images. The research framework of this paper is shown in figure 1. This

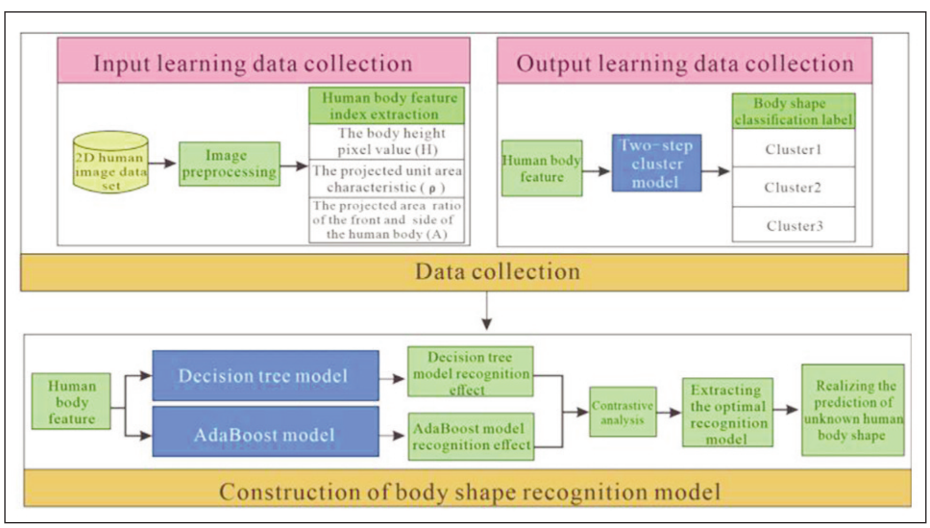

Fig. 1. Framework of the proposed methodology

method realizes the classification and recognition of the body shape without the body size, and it is a body classification and recognition method based entirely on 2D images. The realization of this method is crucial for anthropometric technology based on 2D images and further promotes the development of garment remote customization.

RESEARCH METHOD

Establishment of a 2D image dataset

The 2D body images were obtained from a 3D body database in this study, and a 2D image dataset was established; a total of 430 young women aged 18–25 years were randomly measured, with a height of 145.7–178.6 cm and a weight of 35.6–90 kg. During measurement, the subjects wore tight-fitting underwear, kept their bodies straight, and kept their shoulders straight but not stiff. There were two postures for measurement. The first posture was to stand with the feet apart, arms at a 20° angle to the body, and palms facing inward. The second position was to stand with the arms together and positioned against the sides, with the feet together, while breathing normally and not sucking in the stomach.

2D body characteristic index extraction

Effective characteristic extraction is the premise of body type classification and recognition [15]. In this paper, a human characteristic extraction method based on 2D photos is proposed by using computer vision technology. This characteristic can be used in the classification and recognition of human body shapes in 2D images.

The body height pixel value characteristic extraction (H)

The body height is used as the normalization standard to normalize 2D digital images to eliminate the influence of size factor on body characteristic extraction. Select the maximum height of the sample, and set the distance from the top of the head to the bottom of the feet as P pixels in the body area. In this paper, P = 700, and we normalized the height data by using formula (1), where H is the normalized height, h – the body height of any sample, h_{max} – the maximum value of the body height, and h_{min} – the minimum value of the body height.

$$H = P * \frac{h - h_{min}}{h_{max} - h_{min}} \quad (1)$$

Extraction of the projected unit area characteristic (ρ)

As shown in figure 2, *a* and *c*, the front and side 2D images of the body were M×N in size. After binarization, the body area was white, and we set the pixel value to 1, and the background area was black, and we set the pixel value to 0. Let the height direction of the body be the Y-axis, and the vertical direction of the Y-axis be the X-axis. The cumulative distribution of points with the pixel value of 1 in the X- and Y-axis directions of the body area, that is, the cumulative distribution of pixel value $f(i,j)$ = 1, was calculated using the statistical method as follows:

$$X_{(i)} = \sum_{j=1}^{N} f(i,j) \; (i = 1,2,3,\ldots,M),\; f(i,j) = 1 \quad (2)$$

$$Y_{(j)} = \sum_{i=1}^{M} f(i,j) \; (j = 1,2,3,\ldots,N),\; f(i,j) = 1 \quad (3)$$

Figure 2, *b* and *d* show the histograms of the grey distribution of the binary image of 2D digital photos. The maximum height difference of the distribution of white dots along the X-axis and the Y-axis was calculated as follows:

$$X\_l = \max(X(i)) - \min(X(i)) \; (i = 1,2,3,\ldots,M) \quad (4)$$

$$Y\_l = \max(Y(j)) - \min(Y(j)) \; (j = 1,2,3,\ldots,N) \quad (5)$$

X_l represents the height characteristics of the body, and *Y_l* – the body fat characteristics. The distribution of the grey histogram is different for different body heights, fatness, and thinness. The greater the *X_l*, the higher the height, and the greater the *Y_l*, the fatter the body. However, only using *X_l* and *Y_l* can roughly explain the height and thinness of the body, which is not suitable for comparative analysis. Therefore, we used the projection unit area ρ to represent the average fatness of the body. We set the body height pixel value to be H and the cumulative white point count in the frontal image of the body to be F, and then, ρ was calculated as follows:

$$\rho = \frac{F}{H} \quad (6)$$

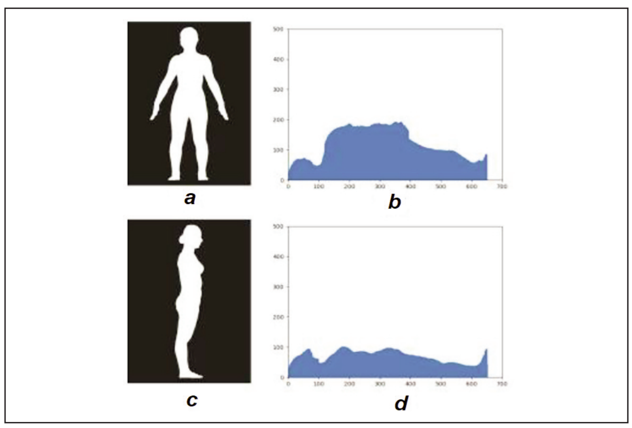

Fig. 2. Binary image and grey histogram of a 2D body image: *a* – front 2D images of the body; *b* – histogram of the grey distribution of the binary image of 2D digital front photos; *c* – side 2D image of the body; *d* – histogram of the grey distribution of the binary image of 2D digital side photo

Extraction of the projected area ratio of the front and side of the body (A)

Only using ρ cannot accurately express the body shape information when classifying the body shape, and the roundness of the torso also affects the body shape and the effect of clothing. According to the Chinese national standard GB/T 16160-2017 "Parts and Methods of Body Measurement for Clothing" and the proportional relationship between human body parts and height, using the local ergodic method determined the side neck point and shoulder endpoint, then the head and neck information of the body was removed along the side neck point, and the arm information was removed along the shoulder endpoints. Also, the ratio of the front and side projection areas of the body was extracted to characterize the degree of roundness of the body. We set the cumulative number of white points on the front of the body as Z and the cumulative number of white points on the side of the body as B. The ratio of Z to B is defined as follows:

$$A = \frac{Z}{B} \tag{7}$$

Body shape recognition method

Decision tree recognition model

Decision tree, including the root node, decision node, and leaf node, is a natural processing mechanism for decision-making based on the tree structure [16]. The leaf node corresponds to the category attribute of the decision tree, and the decision node corresponds to an attribute test. The root node contains the complete set of samples. The path from the root node to each leaf node corresponds to a decision test sequence. Decision tree has the advantages of a simple structure, clear logic, and good interpretability. The best decision tree can be constructed by known prior data to predict the category of unknown data. In this paper, the decision tree ID3 algorithm was used to identify the body shape. This algorithm is a machine learning algorithm first proposed by Quinlan in 1975. It takes information entropy and information gain as the measurement indices of node splitting to study the classification problem.

AdaBoost recognition model

Ensemble learning completes the learning task by constructing and combining multiple individual learners, which is also called a multi-classifier system or committee-based learning. The general structure of ensemble learning is to generate a group of “individual learners” and then combine them with some strategy. Individual learners are usually generated from training data by an existing algorithm. There are two types of integration: homogeneous integration and heterogeneous integration. Homogeneous integration means that all individual learning algorithms are of one type; heterogeneous integration means that individual learners are composed of different types of learning algorithms. The ensemble learning algorithm overcomes the overfitting problem caused by the sampling strategy and improves the overall performance, accuracy, and stability of the machine learning algorithm [17]. In this paper, an AdaBoost homogeneous ensemble learning algorithm based on a decision tree model is proposed for 2D human body shape recognition.

AdaBoost is an efficient ensemble learning method proposed by Yoav Freund. It combines many weak classifiers to create a strong classifier, and there is a strong dependence among individual learners. The algorithm includes an iterative training process of weak classifiers and an integration process of weak classifiers [18, 19]. The steps of AdaBoost are as follows: first, initialize the weight of each sample, train a weak classifier, and calculate the error rate of the classifier. Then, according to the performance of the classifier in the previous iteration, the weight of each sample is updated, the weight of the incorrectly identified sample is increased, and the weight of the correctly classified sample is decreased. The essence of AdaBoost's learning process is to change the weights of samples in constant learning until the error of learning results is zero or the number of learners reaches the preset value and then synthesize the learning results of all weak classifiers according to the weights to output the final results [20]. The algorithm flow is as follows:

a. Determine the decision tree as a weak classifier;
b. Determine a 2D body feature sample training set S: $S = \{(x_1,y_1), (x_2,y_2), \ldots, (x_n,y_n)\}$, $x_i \in X$;
b. The body shape classification label is $y_i \in Y = \{1, 2, \ldots, k\}$;
d. Initialize the weights of the training sets of the samples and endow all training samples with the same initial weights, that is, $w_i = \frac{1}{n}$. Then, the initial weight distribution of the sample is $D_1 = (w_1, w_2, \ldots, w_n) = (\frac{1}{n}, \ldots, \frac{1}{n})$, where D_1 is the initial weight of the training set samples, and n – the number of samples in the training set;
e. Using the weighted sample training set to learn, obtain a weak classifier, $h_m : X \rightarrow Y$;
f. Calculate the classification error rate of the sample training set as follows:

$$e_m = \sum_{i=1}^{n} w_i^{(m)} [h_m(x_i) \neq y_i] \tag{8}$$

g. The weak classifier weight is given by

$$\alpha_m = L_r \left[\ln \frac{1 - e_m}{e_m} + \ln(R - 1) \right] \tag{9}$$

where L_r is the learning rate, and R – the number of the body type;

h. Update the sample weight:

$$w^T = \frac{w^{T-1} \exp(\alpha_T F)}{Z_T} \tag{10}$$

The F condition is used to represent the prediction result of the weak classifier. Here, Z_T is the normalization factor, and its calculation formula is as follows:

$$Z_T = \sum_{i=1}^{m} w_i^T \tag{11}$$

i. The weighted sum of all weak classifiers is

$$f_{(x)} = \sum_{m=1}^{T} \alpha_m h_m(x) \tag{12}$$

j. The final classifier is obtained as follows:

$$H(x) = sign(f(x)) = sign\left(\sum_{m=1}^{T} \alpha_m h_m(x)\right) \tag{13}$$

where T is the number of iterations, and α_m – the weak classifier weight.

RESULTS AND DISCUSSION

Cluster analysis

In this study, the two-step cluster (TSC) model in Statistical Product and Service Solutions (SPSS) software was used to cluster the body shape. The most significant advantage of TSC is that it can automatically calculate the optimal number of clusters, and the classification variables were H, ρ, and A. The body types are divided into three types. Information such as the number of people and the centroid of each type is shown in table 1.

Table 1

CLUSTER RESULTS

Cluster		1	2	3
Sample size		164	162	104
Proportion (%)		38.1	37.7	24.2
The centroid of each element	H	652.68	611.30	632.95
	A	1.54	1.52	1.46
	ρ	105.81	101.87	108.20

As can be seen from table 1, the greater the H of the centroids of the three types of body shapes, the higher the body height, and the closer A is to 1, indicating that the cross-sectional shape of the whole body is closer to the circle, and the greater ρ indicates that the body is fatter. By analysing the centroids of H, A, and ρ, we can divide the three types of body shapes as follows. For the first cluster, H = 652.68 indicates that it is the highest among all body types, A = 1.54 indicates that its cross-sectional shape is the flattest among the three body types, and ρ = 105.81 indicates that it is in the middle of the three clusters; thus, this cluster is called the tall, flat, and medium fatness type. For the second cluster, H = 611.30 indicates that it is the shortest of all body types, A = 1.52 indicates that the cross-sectional shape of its body is close to the standard ellipse, and ρ = 101.87 indicates that it is the thinnest of these three clusters; thus, this is called the short, thin, and medium roundness type. For the third cluster, H = 632.95 indicates that it is of medium height, A = 1.46 indicates that the cross-sectional shape of its body is a relatively round ellipse, and ρ = 108.20 indicates that the body is the fattest among the three clusters; thus, this is called the round, fat, and medium height type.

Body shape recognition

If the feature extraction and classification methods involved in this study are to be applied in practice, the intelligent recognition of body shape is important. Based on Python software, this paper establishes the decision tree model and AdaBoost model to recognize the body shape of unknown females in 2D body images. Training data are usually a large part of the dataset, which is used to learn discriminant rules. The more training data collected, the higher the accuracy of the results. The test data are used to obtain the correct rate of the classifier. In this paper, the ratio of training data to test data was 8:2, that is, 344 groups were randomly selected as training sets, and the remaining 86 groups were test sets. The features used for body shape identification were H, ρ, and A, and the results of body type classification were used as body shape identification labels.

Body shape recognition based on decision tree

We established the ID3 recognition model of the decision tree, trained the features of 2D digital images using the training set, and then tested the recognition effect of the model using the testing set. We set the number of tree nodes to (7, 15) and the number of iterations to 100, and we compared the classification accuracy of different tree nodes to determine the optimal number of tree nodes.

Table 2 shows the classification accuracy corresponding to the number of different nodes. When the number of selected nodes increases, the classification effect of the decision tree model on body shape is improved. When the number of nodes is 12, the classification accuracy of the decision tree model to the test set reaches 93.19%. When the number of nodes exceeds 12, the classification accuracy of the model starts to stabilize.

From the data in the table, it can be seen that the accuracy of the decision tree model in body shape classification is not high. To avoid misjudgement in practical application, it is necessary to improve the classification accuracy of body shape. Ensemble learning algorithms such as AdaBoost can greatly improve the classification effect of weak classifiers; so, this paper attempts to establish a body shape recognition model using AdaBoost.

Table 2

RELATION BETWEEN THE NUMBER OF NODES AND CLASSIFICATION ACCURACY OF DECISION TREE MODEL

Node number	Recognition accuracy rate (%)	Node number	Recognition accuracy rate (%)
7	90.83	11	93.14
8	92.07	12	93.19
9	92.07	13	93.19
10	93.14	14	93.19

Table 3

RELATION BETWEEN THE NUMBER OF NODES AND CLASSIFICATION ACCURACY OF THE ADABOOST MODEL			
Node number	**Recognition accuracy rate (%)**	**Node number**	**Recognition accuracy rate (%)**
7	95.26	11	96.30
8	94.87	12	96.30
9	94.87	13	97.35
10	96.30	14	96.30

Body shape recognition based on the AdaBoost model

In this paper, AdaBoost was used to train the sample data in the training set, and the recognition effect of the model was also tested by the test set. Using the decision tree model as the weak classifier, we initialized the sample weight, set the node number of the weak classifier to (7, 15), and set the number of iterations to 100. The classification accuracy of AdaBoost under different node numbers is shown in table 3.

As can be seen from table 3, when the number of nodes in the decision tree as its weak classifier is 13, the classification effect of the AdaBoost classifier on the test set is 97.35%. After 100 iterations, the AdaBoost algorithm improves the classification accuracy of test sets from 93.19% to 97.35% compared with the decision tree algorithm, and it improves the recognition accuracy by 4.16%. The above analysis proves that the classification effect of AdaBoost is better than that of the weak classifier.

Modelling verification

To verify the superiority of AdaBoost in body shape recognition when the data volume is small and the classification is complex, we adjusted the sample size of the dataset to 362 samples for body shape recognition, and at the same time, we increased the number of clusters for body shape classification and divided the body shape into six clusters. With the same number of nodes and iteration times, the recognition accuracy of the decision tree model is reduced to 81.45% at this time, while that of AdaBoost is 95.8%, which is 14.35% higher than that of the decision tree model. Thus, AdaBoost shows more stable recognition accuracy in the case of few samples and complicated classification.

CONCLUSION

In this paper, 2D digital images of the human body in garment remote customization were taken as the research object, and computer vision technology was used to extract body shape features for classification and recognition. The principles of the decision tree and AdaBoost were deeply analysed. The comparative experiment showed that AdaBoost had high accuracy in recognizing the body shape in 2D images. The following conclusions were drawn:

Using computer vision technology, we extracted the body height pixel value (H), the feature of the projected unit area (ρ), and the feature of the projected area ratio of the front and side of the body (A) as the body feature indices for body type classification and recognition. Using the two-step clustering model, we divided the bodies into the following types: the tall, flat, and medium fatness type; the short, thin, and medium roundness type; and the round, fat, and medium height type. The recognition accuracy rate of 2D body shape in the test set by the decision tree model was 93.19% and that of AdaBoost based on the decision tree was 97.35%. Compared with the decision tree model, the AdaBoost model had higher recognition accuracy, especially when there were many classifications and insufficient data. Moreover, AdaBoost effectively solved the over-fitting problem of recognition. Therefore, the method can be used in human body shape recognition and related fields.

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