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Construction of a prediction model for body dimensions used in garment pattern making based on anthropometric data learning

Kaixuan Liu[a,b,c,d], Jianping Wang[a,b], Edwin Kamalha[c,d], Victoria Li[e] and Xianyi Zeng[c,d]

[a]College of Fashion and Design, Donghua University, Shanghai, China; [b]Key Laboratory of Clothing Design & Technology, Donghua University, Ministry of Education, Shanghai, China; [c]Ecole Doctorale EDSPI, University of Lille 1, Nord de France, Lille, France; [d]GEMTEX Laboratory, ENSAIT, Roubaix, France; [e]Thomas Jefferson High School for Science and Technology, Alexandria, VA, USA

ABSTRACT
Using artificial intelligence to predict body dimensions rather than measuring them physically is a new research direction in apparel industry. If implemented, this technology can reduce costs and improve efficiency. In this paper, we proposed a back propagation artificial neural network (BP-ANN) model to predict pattern making-related body dimensions by inputting few key human body dimensions. In order to construct the proposed model, anthropometric measurements of 120 young females from the northeastern region of China were collected. The data were then used for training and the proposed model. The results showed that the prediction of the developed BP-ANN model is more accurate and stable than that of linear regression (LR) model. As great as the LR model was at pattern making, the BP-ANN model is even better. In the future, the precision of the proposed model can be further improved if the size of the learning data increases. The proposed method can be especially useful in making garment pattern for form-fitting clothing.

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KEYWORDS
Artificial intelligence (AI); anthropometric measurement; 3D body scanning; back propagation artificial neural network (BP-ANN); linear regression (LR)

Introduction

Garment pattern making, also known as garment construction design or pattern cutting, is considered as the highest technical work in the process of clothing design and production. The pattern making of a garment involves three steps. First, pattern makers draw construction lines, based on fashion drawings, on kraft papers. They then cut out these encircled paper pieces. And finally, fabrics are cut out based on the aforementioned shapes (Armstrong, 2011). Pattern making links fashion design and clothing making (Zhang, 2010). Currently, pattern making is still a highly experiential skill.

Garment pattern makers make pattern according to body dimensions. Therefore, anthropometric measurement is indispensable for pattern making (Simmons & Istook, 2003). While some body dimensions are easily measured (height, waist, and hip), others are more difficult, such as crotch width, crotch length, and abdomen. For example, crotch width is defined as the widest part of body crotch; however, it is difficult to be measured and located (Wu, Liu, Wu, & Ding, 2015). Moreover, it is unrealistic for patterns makers to measure all dimensions of a customer from an economic perspective. In order to avoid this obstacle, garment pattern makers calculate all dimensions of a garment by inputting easily acquired dimensions into empirical formulas (Zhang, 2010). Currently, the most popular model for these empirical formulas is the linear regression (LR) model because of its simplicity and practicality.Using the LR model, pattern makers can calculate all dimensions required for pattern making (Chan, Fan, & Yu, 2005). For instance, all the dimensions of a garment in the height direction can be calculated based on human height. However, the relationship between human body dimensions is not always linear. Thus, the LR model is not accurate. When these inaccurate dimensions are used to make garments, many consumers complaint unfit issues of these garments. Although made-to-measure clothing can solve the fitting issues, the cost of this type garments is not affordable to all individuals.

The traditional manual measurement method is not precise because it is heavily dependent on the measurer's judgment. As discussed above, inaccurate anthropometric dimensions will lead to unfit garments (Liu, Li, Chen, & Lu, 2014). In order to measure body dimensions accurately and efficiently, the three-dimensional (3D) body scanner was developed. This device can accurately collect hundreds of body dimensions in a few seconds (Daanen & Ter Haar, 2013; Daanen & Van de Water, 1998). Therefore, it is widely applied in clothing and other relevant fields. However, 3D body scanner has some disadvantages. It is expensive and its size is enormous. Therefore, it has to be placed in a spacious room. To store the processed data, the 3D body scanner needs a huge capacity (Uhm, Park, & Park, 2015). Furthermore, the process requires the subjects to wear underwear, which may make them uncomfortable and lead to their refusal to be measured. These disadvantages discourage many middle and small-scale clothing enterprises from purchasing this device.

With an increase in demand for form-fitting garments, consumers are requesting more personalized garments (Apeagyei &

CONTACT Kaixuan Liu ✉ 2017vli@tjhsst.edu

Otieno, 2007; Boynton, 1998). As personalized garments require more accurate body dimensions, it is necessary to find a new method to obtain body dimensions that is less time-consuming, more accurate, and less expensive than current methods (Liu et al., 2014). In order to achieve this goal, two research directions are proposed: to reduce cost of 3D body scanner or to use a more precise algorithms to predict body dimensions (Liu et al., 2014). The most advantage of the latter one is inexpensive. Currently, using some indexes predicting others indexes is widely applied in many fields, for example, material properties prediction (Ahmad, 2015; Almetwally, Idrees, & Hebeish, 2014; Behera & Guruprasad, 2012; Upadhyay, Jain, & Mehta, 2013; Vadood, Johari, & Rahai, 2015), finance-related prediction (Gordini, 2014; Lin, Liang, Yeh, & Huang, 2014; Rather, Agarwal, & Sastry, 2015), disease prediction (Liu et al., 2015; Qian, Wang, Cao, Li, & Jiang, 2015), and action and image recognition (Cheng, Dai, Liu, & Zhao, 2016; Wu, Lyu, Hu, & Ji, 2015). Based on these reasons, we selected a mathematic algorithm to predict body dimensions. We aim to improve the accuracy of body dimensions prediction for garment pattern making.

In recent years, artificial intelligence is widely applied in all fields and industry, especially in knowledge engineering, expert system, and artificial neural networks (Sriram, 2012). However, the traditional pattern making fails to adequately utilize the expert knowledge (Guo, Wong, Leung, & Li, 2011). Clothing industry, a labor-intensive industry, faces many issues, such as the rising cost of labor and raw materials (Scott, 2006). Using artificial intelligence technology to predict body dimensions rather than measuring them is a new research direction in apparel industry. If implemented in the clothing industry, artificial intelligence can save time, cut costs, and improve efficiency. Chan et al. proposed back propagation artificial neural network (BP-ANN) and multiple linear regression model to predict skirt's dimensions for pattern making by learning from 3D anthropometric data (Chan, Fan, & Yu, 2003). However, their research only focused on the dimension prediction of a specific garment. Moreover, they used body dimensions to predict garment pattern's dimensions. Garment pattern dimensions are human body dimensions with the addition of some ease allowances. However, these ease allowances are difficult to established and are usually set by the more experienced pattern makers. In addition, these allowances vary significantly with garment style. Therefore, the method of predicting garment pattern's dimensions rather than body dimensions is not reliable. With its arbitrary nonlinear expressiveness property, BP-ANN was adopted to construct lower body dimension prediction model in this research. The inputs of the proposed model are height, hip, and waist measurements and the outputs of the model are other body dimensions that are related to pattern making.

The main experiment in this research was designed to collect anthropometric data. Due to the advantages of 3D body scanner, we used it to collect the anthropometric data of 120 young women who are from the northeastern region of China. The age of the study group is between the ages 20 and 25 and the height ranges between 145 and 175 cm. In this research, we focused mainly on predicting lower body dimensions for the pattern making of lower body clothing. Thus, 13 body dimensions of each measuring object, which are essential for pattern making of lower clothing, were collected. The collected data were used for the machine learning of the proposed model. The goal of this research is to use BP-ANN model in place of the 3D body scanner thereby reducing the cost significantly.

For a clear article structure, the following sections were organized as follows. Section 'General Schemes' introduced the general scheme of our research. Sections 'Modeling of the Relation between Key Human Body Dimensions and Pattern Making-related Body Dimensions' presented the anthropometric data collection. Section 'Learning Data (Anthropometric Data) Acquisition and Preprocessing' expounded the construction of the body dimension prediction model based on BP-ANN. In Section 'Validation and Example of Application', we evaluated the prediction accuracy of the proposed model and gave a practical application of the proposed model for garment pattern making. Finally, some conclusions and possible further works were conducted in Section 'Conclusion'.

General schemes

The general scheme of body dimension prediction based on BP-ANN was described in Figure 1. The implementation process was as follows:

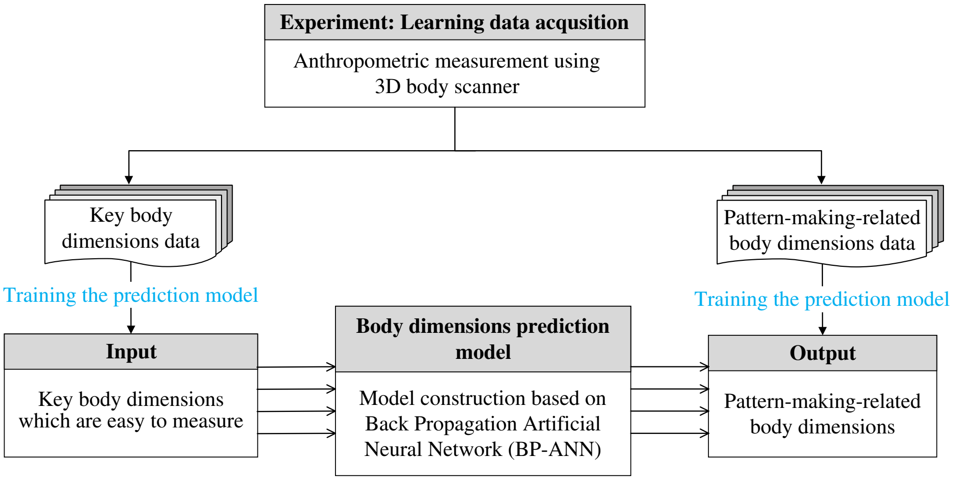

Figure 1. Body dimension prediction model.

- A body dimensions prediction model was developed based on BP artificial normal network. Inputs of the model were key dimensions of human body. The key dimensions referred to the dimensions are necessary to make pattern and are easy to measure (height, bust, and waist). Outputs of the model were all dimensions related to pattern making, such as waist width, knee height.
- An anthropometric measurement experiment was carried out to collect learning data.
- The collected data were divided into two parts: input learning data (key body dimensions data) and output learning data (pattern making-related data).
- The body dimension prediction model was trained by the input and output learning data.
- We only measured a new customer's key body dimensions and inputted the key body dimensions into the trained model. Then the proposed model without any anthropometric measurement could predict the pattern making-related body dimensions. Finally, garment patterns were made according to the predicted body dimensions.

Modeling of the relation between key human body dimensions and pattern making-related body dimensions

Formalization

Compared with LR model, the BP-ANN model provided powerful potential in nonlinear fitting and prediction (Zhang, Eddy Patuwo, & Hu, 1998). As the relationships between body dimensions are nonlinear rather than linear, the BP-ANN model was adopted to construct the relations between key human body dimensions and pattern making-related body dimensions. A body dimension prediction model based on BP-ANN was constructed as showed in Figure 2. It consisted of three layers: input layer, hidden layer, and output layer. The inputs of the proposed model were key body dimensions; and the outputs of the proposed model were pattern making-related dimensions. The concepts and data involved in the modeling process were formalized as follows:

Let n be a number of neurons in input layers;

Let p be a number of neurons in hidden layers;

Let q be a number of neurons in output layers;

Let $bd = \left(bd_1, bd_2, \ldots, bd_n\right)$ be a set of key human body dimensions input. In this research, $n = 3$, refers to a set of n key body dimensions measured by 3D body scanner; there are 'height', 'hip girth', and 'waist girth', respectively.

Let $pd = \left(pd_1, pd_2, \ldots, pd_m\right)$be a set of expected pattern making-related body dimensions output. In this research, $m = 10$ refers to a set of m pattern making-related body dimensions measured by 3D body scanner; the set includes 'crotch height', 'waist height', 'hip height', 'abdomen height', 'total crotch length', 'knee height', 'crotch width', 'abdomen girth', 'thigh girth', and 'knee girth'.

Let $hi = \left(hi_1, hi_2, \ldots, hi_p\right)$ be a set of hidden layer's input vector;

Let $ho = \left(ho_1, ho_2, \ldots, ho_p\right)$ be a set of hidden layer's output vector;

Let $yi = \left(yi_1, yi_2, \ldots, yi_m\right)$ be a set of output layer's input vector;

Let $yo = \left(yo_1, yo_2, \ldots, yo_m\right)$ be a set of output layer's output vector; In this research, $m = 10$, it refers to a set of m pattern making-related body dimensions measured by 3D body scanner; there are 'crotch height', 'waist height', 'hip height', 'abdomen height', 'total crotch length', 'knee height', 'crotch width', 'abdomen girth', 'thigh girth' and 'knee girth', respectively.

Let w_{ih} be a linked weights between input layer and middle layer;

Let w_{ho} be a linked weights between hidden layer and output layer;

Let b_n be a threshold values of hidden layer's neurons;

Let b_o be a threshold values of output layer's neurons;

Let $k = 1, 2, \ldots, m$ be sample size;

Let $f(\cdot)$ be activation function;

Let $ef = \frac{1}{2}\sum_{o=1}^{m}\left[pd(k) - yo_o(k)\right]^2$ be error function.

Construction of body dimension prediction model

The model was constructed using BP-ANN and was composed of nine steps.

Step 1: Initialization of the network

Assign random numbers between interval $(-1, 1)$ to all linked weights, respectively, set the error function e, and give calculation accuracy value ε, and maximum learning time T.

Step 2: Select the kth inputting sample $x(k)$ and its corresponding expected output $d_o(k)$ randomly.

$$bd(k) = \left(bd_1(k), bd_2(k), \ldots, bd_n(k)\right)$$

$$pd(k) = \left(pd_1(k), pd_2(k), \ldots, pd_m(k)\right)$$

Step 3: Calculate hidden layer's neurons input and output values.

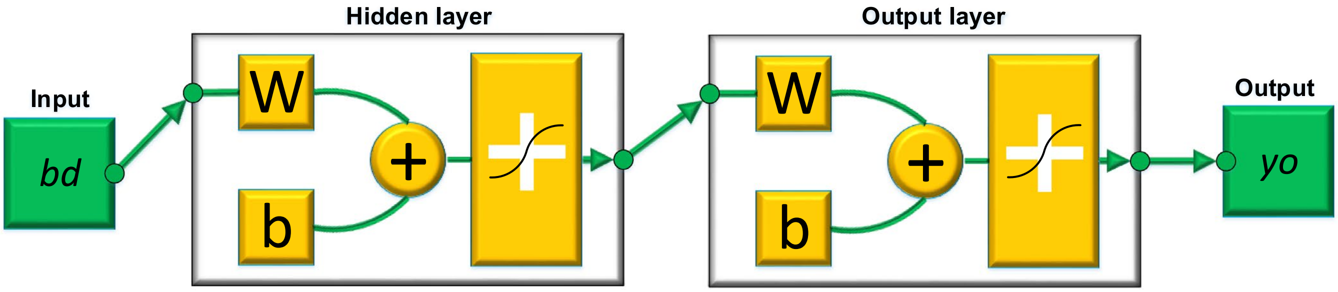

Figure 2. Three layers' back propagation artificial neural network.

$$hi_h(k) = \sum_{i=1}^{n} w_{ih} bd_i(k) - b_h, \quad h = 1, 2, \ldots, p$$

$$ho_h(k) = f\left(hi_h(k)\right), \quad h = 1, 2, \ldots, p$$

$$yi_o(k) = \sum_{h=1}^{p} w_{ho} ho_h(k) - b_o, \quad o = 1, 2, \ldots, m$$

$$yo_o(k) = f\left(yi_o(k)\right), \quad o = 1, 2, \ldots, m$$

Step 4: Calculate partial derivative $\delta_o(k)$ of error function with respect to output layer's neurons according to expected and actual outputs.

$$\frac{\partial ef}{\partial w_{ho}} = \frac{\partial ef}{\partial yi_o} \frac{\partial yi_o}{\partial w_{ho}}$$

$$\frac{\partial yi_o(k)}{\partial w_{ho}} = \frac{\partial\left(\sum_h^p w_{ho} ho_h(k) - b_o\right)}{\partial w_{ho}} \frac{\partial yi_o}{\partial w_{ho}} = ho_h(k)$$

$$\frac{\partial e}{\partial yi_o} = \frac{\partial\left(\frac{1}{2}\sum_{o=1}^{m}\left(pd(k) - yo_o(k)\right)\right)^2}{\partial yi_o}$$

$$= -\left(pd(k) - yo_o(k)\right) yo'_o(k)$$

$$= -\left(pd(k) - yo_o(k)\right) f'\left(yi_o(k)\right)$$

$$\triangleq -\delta_o(k)$$

Step 5: Calculate partial derivative $\delta_h(k)$ of error function with respect to hidden layer's neurons according to hidden layer's output, input layer's $\delta_o(k)$, and hidden-to-output layers' linked weights.

$$\frac{\partial ef}{\partial w_{ho}} = \frac{\partial ef}{\partial yi_o} \frac{\partial yi_o}{\partial w_{ho}} = -\delta_o(k) ho_h(k)$$

$$\frac{\partial ef}{\partial w_{ih}} = \frac{\partial ef}{\partial yi_h(k)} \frac{\partial yi_h(k)}{\partial w_{ih}}$$

$$\frac{\partial hi_h(k)}{\partial w_{ih}} = \frac{\partial\left(\sum_{i=1}^{n} w_{ih} bd_i(k) - b_h\right)}{\partial w_{ih}} = bd_i(k)$$

$$\frac{\partial ef}{\partial hi_h(k)} = \frac{\partial\left(\frac{1}{2}\sum_{o=1}^{m}\left(pd(k) - yo_o(k)\right)^2\right)}{\partial ho_h(k)} \frac{\partial ho_h(k)}{\partial hi_h(k)}$$

$$= \frac{\partial\left(\frac{1}{2}\sum_{o=1}^{m}\left(pd(k) - f\left(yi_o(k)\right)\right)^2\right)}{\partial ho_h(k)} \frac{\partial ho_h(k)}{\partial hi_h(k)}$$

$$= \frac{\partial\left(\frac{1}{2}\sum_{o=1}^{m}\left(pd(k) - f\left(\sum_{h=1}^{p} wh_o ho_h(k) - b_o\right)^2\right)\right)}{\partial w_{ho}(k)} \frac{\partial ho_h(k)}{\partial hi_h(k)}$$

$$= -\sum_{o=1}^{m}\left(pd(k) - yo_o(k)\right) f'\left(yi_o(k)\right) w_{ho} \frac{\partial ho_h(k)}{\partial hi_h(k)}$$

$$= -\left(\sum_{o=1}^{m} \delta_o(k) w_{ho}\right) f'\left(hi_h(k)\right) \triangleq -\delta_h(k)$$

Step 6: Amend the linked weight $w_{ho}(k)$ according to hidden layer neurons' output values and output layer neurons' $\delta_o(k)$.

$$\Delta w_{ho}(k) = -\mu \frac{\partial ef}{\partial w_{ho}} = \mu \delta(k) ho_h(k)$$

$$w_{ho}^{N+1}(k) = w_{ho}^{N} + \eta \delta_o(k) ho_h(k)$$

Step 7: Amend the linked weight $w_{ih}(k)$ according to input layer neurons' output values and hidden layer neurons' $\delta_h(k)$.

$$\Delta w_{ih}(k) = -\mu \frac{\partial ef}{\partial w_{ih}} = -\mu \frac{\partial ef}{\partial hi_h(k)} \frac{\partial hi_h(k)}{\partial w_{ih}} = \partial_h(k) bd_i(k)$$

$$w_{ih}^{N+1}(k) = w_{ih}^{N} + \eta \delta_h(k) bd_i(k)$$

Step 8: Calculate global error E.

$$E = \frac{1}{2T} \sum_{k=1}^{T} \sum_{o=1}^{m} \left(pd(k) - y_0(k)\right)^2$$

Step 9: Check whether the network error meets the requirement.

If either the error is within the limit of presupposed precision or the learning times are greater than the predefined maximum, the running model is terminated. Else, enter the next round of learning by returning to step 3 with the next learning sample and its corresponding expected outputs.

Thus, the pattern making-related body dimensions can be predicted using the researched model by inputting key body dimensions. The generated dimensions can be then used in garment construction.

Learning data (anthropometric data) acquisition and preprocessing

Measuring tools

In this research, we chose 3D body scanner (Lectra Vitus Smart) to measure body dimensions. This method is more accurate and efficient compared to the traditional measuring method (Daanen & Ter Haar, 2013; Daanen & Van de Water, 1998). The 3D body scanner system of Lectra Vitus Smart uses two charge-coupled device cameras and one laser gage to scan and photograph human body. The body dimensions of the subjects are then extracted automatically.

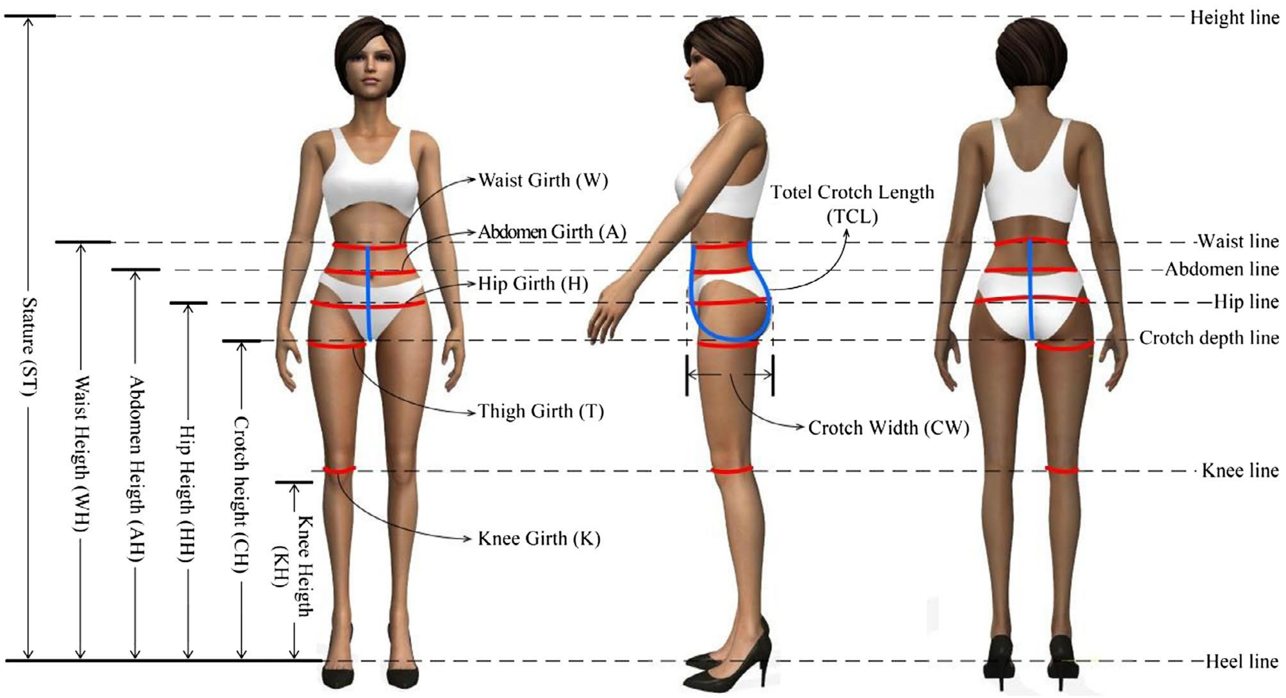

Figure 3. Legend of measurement dimensions.

Table 1. Definitions of anthropometric items.

Items	Abbr.	Definitions
Height	ST	The vertical distance measured from the crown to the soles of feet with the subject standing upright and the feet together without wearing shoes
Waist height	WH	The vertical distance measured from the waist to soles of feet
Abdomen height	AH	The vertical distance measured from the abdomen to soles of feet
Hip height	HH	The vertical distance measured from the midpoint of the crotch to soles of feet
Crotch height	CH	The vertical distance measured from the midway point of the crotch to the soles of feet
Knee height	KH	The vertical distance measured from the knee to the soles of feet
Waist girth	W	The length of measuring around the most prominent part of abdomen horizontally
Abdomen girth	A	The length of measuring around the slenderest part of waist horizontally
Hip girth	H	The length of measuring around the fullest part of hip horizontally
Thigh girth	T	The length of measuring around the fullest part of thigh horizontally
Knee girth	K	The length of measuring around the knee horizontally
Total crotch length	TCL	The distance measured from the center point of the front body at the waist level, through the crotch, to the center point of the back body at the waist level
Crotch width	CW	The horizontal distance between the front rise and the back rise

Subjects

In this research, the subjects were 120 young women from the northeastern region of China whose heights range between 145 and 175 cm, between 20 and 25 years old, and of Han ethnic.

Anthropometric measurement

The 3D body scanner extracted numerous body dimensions from each subject. Since this research only focused on the lower body's dimension prediction, 13 body dimensions closely related to lower body pattern making were chosen to study. They were waist, hip, height, waist height, hip height, etc., as shown in Figure 3. The operational definitions of these 13 body dimensions were given in Table 1 (Wu et al., 2015).

Anthropometric data preprocessing

Data are generally flawed if not processed properly beforehand (Han, Kamber, & Pei, 2011). Using the method of 3σ-rule (Han et al., 2011), we were able to detect some outliers. However, we realized the presumed outliners were not mistakes but special dimensions after rechecking the original data. Special body dimensions do exist in data and population, but for the purpose of this study, these special dimensions, which accounted for about 12% of total sample size, were excluded. Finally, a total of 106 samples were used in this research (Table 2).

Validation and example of application

Validation

We adopted the BP-ANN with three layers to build our prediction model because it is able to use simple nonlinear transfer functions to approximate nonlinear functions with precision, The S-tangent function was implemented in the neural transferring function in the middle hidden layer and the S-logarithmic function was utilized in the output layer. The data shown in Table 2 were the output of the experiment mentioned section 'Modeling of the Relation between Key Human Body Dimensions and

Table 2. Anthropometric data (unit: cm).

	Input learning data			Output learning data									
SN	ST	H	W	CH	WH	HH	AH	TCL	KH	CW	A	T	K
1	151.5	81.6	58.8	64.8	93.4	75.9	86.2	64.5	39.0	17.9	66.9	45.6	33.3
2	152.3	93.5	73.7	64.8	93.7	75.2	88.4	74.4	40.3	20.2	83.7	56.4	38.3
3	152.3	87.3	66.2	66.4	93.5	76.2	86.9	69.3	40.0	19.8	73.7	49.9	34.7
4	153.0	87.9	68.4	65.6	94.3	76.4	87.3	70.7	40.3	19.6	78.0	50.4	35.6
5	153.9	90.4	69.4	67.6	94.7	77.1	88.1	70.8	40.3	19.8	77.5	54.8	35.7
6	154.4	86.4	67.5	69.1	94.4	76.9	89.5	67.5	40.0	19.3	71.8	50.2	35.8
7	154.5	96.2	70.2	67.2	97.3	79.6	88.8	72.8	41.0	21.8	80.9	52.7	38.1
8	154.8	88.6	67.1	70.5	96.4	77.9	90.1	71.3	40.8	18.4	74.9	53.4	35.9
9	154.8	83.4	58.3	71.1	95.0	77.2	89.1	65.6	41.1	18.3	68.2	43.4	33.0
10	155.4	93.8	69.8	66.7	96.4	78.4	90.5	69.7	41.3	20.1	83.3	52.6	35.5
11	155.5	87.1	69.6	69.4	95.9	78.2	90.1	72.0	41.1	19.2	79.1	50.3	34.2
12	156.1	85.6	69.0	68.9	97.0	79.8	90.7	71.9	41.4	19.5	75.1	50.3	36.0
13	156.1	82.9	59.3	72.6	97.2	79.2	90.8	67.4	40.3	19.4	68.3	45.5	32.2
14	156.2	78.0	61.0	71.3	98.2	80.5	91.7	67.5	42.2	17.2	65.0	42.4	31.6
15	156.2	87.0	64.6	70.7	96.7	79.1	90.4	67.0	41.9	19.3	71.7	49.4	35.3
16	156.3	95.6	73.7	65.4	96.6	78.8	89.9	71.8	42.0	20.0	81.4	50.2	39.7
17	156.3	86.5	62.1	68.8	97.1	78.8	90.3	71.3	41.0	18.3	71.2	49.1	35.6
18	156.9	91.6	69.7	70.9	96.2	77.7	90.2	70.6	42.4	19.6	79.2	54.8	37.8
19	156.9	85.2	60.4	70.2	99.1	80.3	91.6	68.4	41.3	18.2	70.6	48.3	34.1
20	156.9	93.2	67.5	67.3	98.1	80.1	91.2	71.2	41.7	20.0	76.1	53.4	36.9
21	157.7	84.1	67.0	71.5	99.0	81.3	93.0	67.5	42.9	18.2	75.4	47.0	34.2
22	157.7	97.8	75.3	69.1	97.8	78.3	91.4	76.5	42.0	20.4	85.7	56.6	40.1
23	157.9	95.5	74.5	69.3	98.9	79.4	91.8	75.6	42.9	19.9	86.2	57.6	41.5
24	157.9	90.1	67.9	70.5	98.7	80.3	92.0	71.9	43.9	19.4	76.0	51.2	37.6
25	157.9	96.5	71.5	68.0	97.5	78.3	91.0	76.1	42.0	19.8	84.4	56.3	38.0
26	158.0	97.4	80.6	70.0	98.5	80.5	91.5	75.8	42.8	22.0	86.3	59.6	42.1
27	158.0	91.9	68.6	68.8	98.7	80.8	92.0	70.8	41.9	20.6	79.8	50.9	35.0
28	158.7	95.1	76.2	69.9	98.2	80.2	91.7	72.8	41.6	20.5	83.9	55.0	39.4
29	158.7	92.3	71.0	72.2	99.3	81.4	92.4	72.4	41.0	20.0	77.9	51.5	37.0
30	158.7	89.8	67.3	66.3	99.2	81.5	92.2	75.7	42.7	19.4	76.3	51.7	38.3
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106	173.2	92.6	65.5	80.7	109.4	89.9	102.6	75.5	47.8	18.6	79.8	53.0	35.7

Notes: SN is sample number. For ST, H, WH, AH, HH, CH, KH, A, T, K, CW, TCL, please refer to Figure 3 and Table 1. The samples are too many; we only show a part of the data.

Pattern Making-related Body Dimensions'. There were a total of 106 subjects involved in the experiment: 74 were for training the proposed model and the rest was for validating and testing the model. The number of the hidden layer's neurons influences the accuracy of prediction. After multiple trials and testing, we found the training sample error was at its minimum when the number of hidden layer's neuron was three.

The mean squared error (MSE) and regression *R* values (*R*) of BPANN and LR were shown in Table 3. MSE was the average squared difference between outputs and targets. The lower the value of MSE, the more accurate a prediction would be. *R* was the correlation between outputs and targets. An *R* absolute value of '1' means a close relationship while '0' indicates a random relationship. Compared with those of BP-ANN, the MSE and *R* values of LR fluctuate wildly, indicating that the consistency of the BP-ANN model (Table 3): the total mean squared error (TMSE) of BP-ANN model was smaller than that of the LR model and mean regression (MR) value of BP-ANN model was greater than that of the LR model. The results of the experiment showed that the dimension prediction of BP-ANN model is more accurate than that of the traditional model.

It was evident from the analysis above that the BP-ANN model is better than the traditional LR model in predicting measurements for pattern making. In the future, the precision of the proposed model can be further improved with a larger learning data.

Table 3. Mean squared error and regression *R* values of the proposed neural network prediction.

Model type		Sample number	MSE	*R*	TMSE	MR
BP-ANN	Training	74	2.37	0.98	2.06	0.98
	Validation	16	1.84	0.99		
	Testing	16	1.96	0.99		
LR	ST and WH	106	2.16	0.98	3.60	0.87
	ST and AH	106	2.26	0.98		
	ST and HH	106	2.57	0.97		
	ST and CH	106	5.35	0.85		
	ST and KH	106	2.32	0.93		
	H and A	106	4.57	0.89		
	H and T	106	3.02	0.91		
	H and K	106	2.89	0.74		
	H and CW	106	1.19	0.80		
	H,ST and TCL	106	9.62	0.66		

Notes: BP-ANN is back propagation artificial neural network; LR is linear regression; MSE is mean squared error; *R* is regression *R* values; TMSE is total mean squared error; MR is mean regression *R* values. For ST, H, WH, AH, HH, CH, KH, A, T, K, CW, TCL, please refer to Figure 3 and Table 1.

Application

A subject's height was 164.9 cm, hip girth was 99.3 cm, and waist girth was 76.4 cm, respectively. Therefore, in this example $bd = (164.9, 99.3, 76.4)$. BP-ANN model was used for predicting the customer's body dimensions. The real body dimensions are as follows:

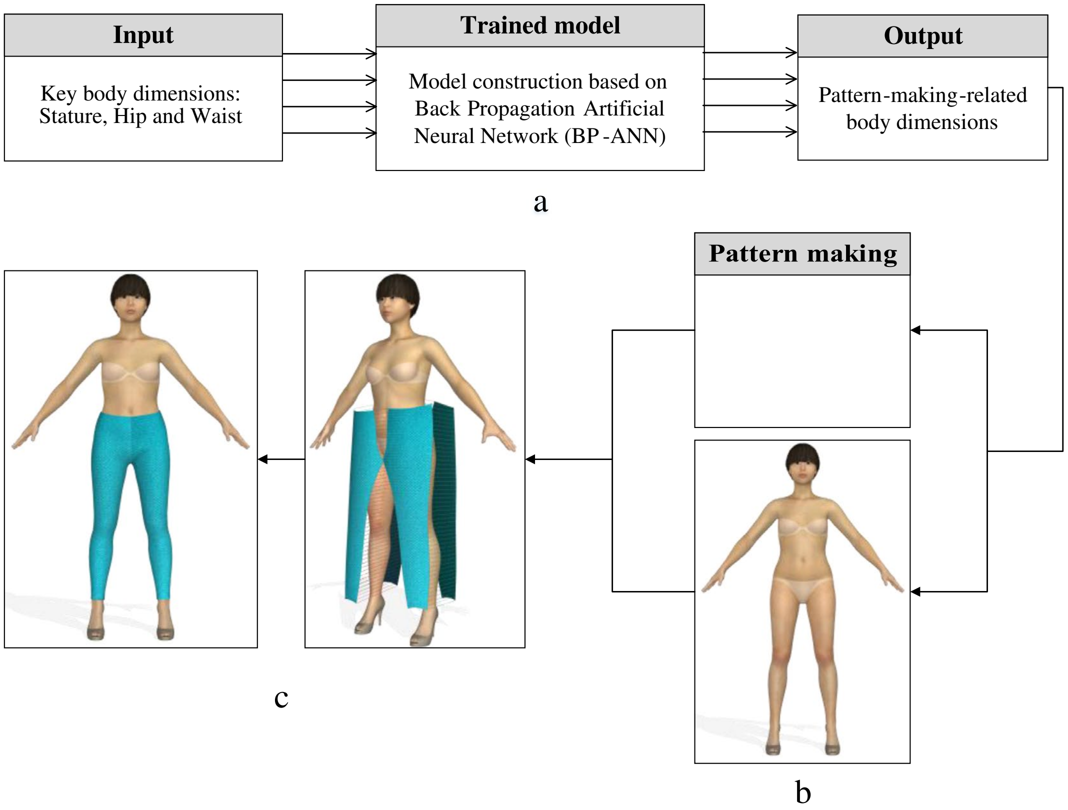

Figure 4. Pattern making and virtual try-on using body dimension predicted by BP-ANN model.

$$pd = (70.3, 104.6, 86.3, 97.2, 77.1, 44.1, 21.2, 88.0, 58.2, 38.9)$$

The predicted body measurements of BP-ANN model were as follows:

$$yo = (72.7, 103.6, 85.3, 97.2, 76.2, 44.7, 21.3, 87.8, 58.3, 39.8)$$

By inputting key body dimensions (height, hip girth, and waist girth), the proposed model can predict the pattern making-related body dimensions efficiently and accurately (Figure 4(a)). The predicted measurements can be then used for making virtual pants patterns (Figure 4(b)). Finally, the assembled pattern was tried on a virtual avatar to test the fit of the pants (Figure 4(c)).

Conclusion

In this paper, we proposed a body dimensions prediction model based on BP-ANN. Compared with LR model, the BP-ANN model had a greater potential in nonlinear fitting and prediction. Because the 3D body scanner can collect anthropometric data accurately and efficiently, we used the data collected by 3D body scanner to train the BP-ANN model for high prediction accuracy. Compared with traditional manual measurement or 3D body scanning, the proposed method can predict the pattern making-related body dimensions more accurately and efficiently. The results showed that the prediction accuracy and stable of BP-ANN model was better than that of the currently used linear regression (LR) models.

Based on the proposed model, we can achieve a computer-aided human body dimension recommendation system. The pattern makers only input customer's key body dimensions into the proposed model and receive accurate all pattern making-related body dimensions instantly. The result of this research can increase the efficiency of pattern making and improve the fit of clothing significantly.

The research data utilized in the experiment were limited to a small age range (25–29 years old), ethnic (Han), and region (northeastern region of China). However, the average body dimension varies for different ages, ethnics, races, geographical regions, etc. Further research can be conducted with changes in aforementioned factors. Although our research mainly focused on the prediction of lower body dimension for bottoms pattern making, the proposed method also can be applied to the upper body or whole body dimensions prediction.

Disclosure statement

No potential conflict of interest was reported by the authors.

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