Garment Fit Evaluation for Fashion Design and Manufacturing

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Garment fit evaluation for fashion design and manufacturing

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Abstract

Currently, garment fit evaluation is one of the biggest bottlenecks for fashion design and manufacturing. In this paper, we proposed a garment fit prediction model using data learning technology, such as Back Propagation Artificial Neural Networks (BP-ANNs), Random Forest, Bayesian Classifier. The inputs of the proposed model are digital clothing pressures measured by virtual try-on; while the output of the model is one of the three fit conditions- tight, fit or loose. In order to acquire reliable learning data, virtual and real try-on experiments were carried out to collect input and output learning data respectively. After learning from the collected input and output experimental data, the proposed model can predict garment fit rapidly and automatically by inputting digital clothing pressures measured by virtual try-on. Test results showed that the prediction accuracies of data-learning-based garment fit evaluation methods are much better than that of traditional methods.

Key words:

Fit evaluation; clothing pressure; data learning; BP-ANNs; Random Forest; Bayesian classifier; Discriminant Analysis; virtual try-on

1.0 Introduction

The issues of garment fit always run through the entire fashion design and manufacturing and sales [1, 2]. In fashion design process, designers and pattern makers need to evaluate garment fit for garment products optimization [3]. In the process of garment manufacturing, designers need to check whether the garment fits [1]. In garment retail field, garment fit is the issue that consumers care most. No matter how beautiful garments are, how excellent fabrics are, customers still do not purchase the garments if they are unfit [1]. Currently, more and more people buy garments on line [4]; however, the bottleneck, how to evaluate garment fit, hampers the development of clothing e-business [5]. Researches showed that more than 50% customers are dissatisfaction with garment fit [6]. High prediction accuracy of garment fit evaluation can decrease the return and exchange ratio significantly. In physical stores, the customers can try on garments to check whether the selected garments are fit or not. Unlike the physical stores, garments bought on line cannot be tried on [7, 8]; thus, customers or sellers only evaluate garment fit roughly according to the previous experience. The experience-based evaluation results are neither accurate nor scientific. Therefore, how to predict garment fit without real try-on is one of main problems that must be solved for clothing industry.

To solve the problem of garment fit evaluation, we should first understand what fit is. There are many factors influence garment fit; nevertheless, what is fit? Up to now, this concept has not been defined exactly. By summarizing fit definitions, clothing fit mainly includes two aspects: aesthetic fit and comfort fit. Comfort fit is mainly related to fabric materials and manufacturing processes, while aesthetic fit is mainly determined by fashion styles. Meanwhile the other design factors such as garment patterns, body dimensions influence either aesthetic fit or comfort fit [9-13]. In this research, we only study on the evaluation of the garment physiological fit. Specifically, the aspect of physiological fit is caused by garment size.

Clothing tightness or looseness is the most intuitive manifestation of fit problem caused by size. Traditional garment fit evaluation includes fit evaluation by real and virtual try-on. In the aspect of real try-on, there are two methods to evaluate garment fit currently. One approach is trying on a dress form, and a designer evaluates whether the garment is fit or not according to his experience. The evaluation result depends on the designer's level. Garment design process mainly adopts this way to evaluate garment fit. The other approach is trying on a live model, and the wearer directly evaluates the garment fit according to his feeling. Garment sales in physical shop mainly adopt this way to evaluate garment fit. As the evaluation result of this method is very accuracy, designers sometimes also adopt this way to evaluate garment fit.

The biggest drawback of using real try-on to evaluate garment fit is the need to make real clothes. With the development of technology, the virtual try-on technology has been proposed to evaluate garment fit in a virtual environment. This technology simulates garment making process and uses garment patterns to model a 3D garment

without making real garment [14-16]. A wearer can feel whether a garment is fit by real try-on; however, virtual try-on cannot [17]. Therefore, some supplementary means were proposed to evaluate garment fit of virtual try-on. At present, there are two methods to do so. One approach is that the visual evaluation carried out on a 3D garment by fashion designers [18, 19]. In actual operation, some experienced designers use pressure map, stress map and fit map generated by virtual try-on software for visual assessment of garment fit. However, these virtual try-on applications, are strongly dependent on mathematical models used in the software [20], cannot give high accurate garment fit evaluation. Obviously, the subjective visual evaluation is neither so accurate nor convincing. The other approach is to measure the ease allowances or air layer thickness, which are between the human body and the garment [21]. Then, evaluators analyze these measured indicators to evaluate garment fit based on their own empirical knowledge.

Garment fit is influenced by fashion style [13], garment pattern [22], body shape [23], body dimensions [9, 24, 25], fabric material [26], and so on. The traditional garment fit evaluation uses ease allowance or air layer thickness to evaluate garment fit. The ease allowance or air layer thickness can neither reflect the fitting feeling when it is less or equal to zero (tight garment style), nor does it take into account fabric properties. With the same value of ease allowance or air layer thickness, the fitting effects will be different if the fabrics are different. Evidently, ease allowance or air layer thickness only, is not enough for characterizing the fitting effects of a garment try-on. The real try-on can judge whether garment fit or not directly; however, the most disadvantage of this method requires people to participate physically in the evaluation process and making real garment. Due to the technical restrictions of real try-on related to real garment production and participation of suitable human subjects, the virtual try-on is proposed to evaluate garment fit. However, these virtual try-on applications, are strongly dependent on mathematical models used in the software [20], cannot give high accurate garment fit evaluation. Moreover, the visual evaluation of virtual try-on needs related empirical knowledge. This results in that the predicted results dependent entirely on subjective factors of designers, like experience, personal preference, etc. Obviously, the subjective visual evaluation is neither so accurate nor convincing.

The emergence of artificial intelligence, data learning and mining technologies provides new approaches to solve the issues of garment fit evaluation. These technologies have been widely applied in the field of clothing and textile over last decade [27], such as, sensory evaluation of textile and related products [18, 28], garment fit and comfort prediction [1, 29], optimization of woven fabric parameters [30], size system [31, 32], intelligent systems of fashion design [33], garment production management [34]; apparel retail [35], clothing image recognition, and supply chain management [36]. Compared to classical methods, intelligent approaches are usually more capable of 1) solving nonlinear problems; 2) processing both numerical and linguistic attributes; 3) modeling human expert reasoning so as to

produce correct and straightforward interpretation of results; and 4) computing with data of small quantity and without need of any preliminary or additional information like probabilistic distributions in statistics. Garment fit evaluation is a non-linear problem. Nonlinear models are widely used to solve the problems of prediction and evaluation in various industries . Due to these advantages of intelligent approaches, we propose to a data-learning-based method to evaluate garment fit. The aim of this research is to evaluate garment fit accurately without real try-on, and realize automatic and intelligent garment fit evaluation. Thus, clothing product developers or sales staffs can reduce the cost of product development or sales by reducing the number of real try-on.

2.0 Methodology

2.1 Input Learning Data Collection (Experiment I)

We selected digital clothing pressures generated by virtual-try-on software as input items in the previous introduction. The concrete implement scheme of input learning data collection is indicated in Figure 1, Garments $g_1, g_2, \dots, g_m, g_{m+1}, \dots, g_{m+n}, g_{m+n+1}, \dots, g_{m+n+s}$ were mapped respectively with k measuring points. All garments' digital clothing pressures were measured according to the k measuring points. For example, digital clothing pressures of garment j were represented as $x_j^1, x_j^2, \dots, x_j^k$. Finally, we measured digital clothing pressures of garments $g_1, g_2, \dots, g_{m+n}$. According to the result of Experiment I, the digital clothing pressure data PD was divided into three sets, p_{fit} , p_{tight} and p_{loose} . We used the three sets of data as input learning data to train the proposed model.

Figure 1. Input learning data collection (digital clothing pressures).

2.2 Output Learning Data Collection (Experiment II)

For a reliable data, we collected output learning by real try-on. The concrete implementation scheme is as follows (Figure 2), wearers tried on all garments in the database. Finally, all the garments were divided into three categories: fit garments $g_1, g_2, \dots, g_m$, tight garments $g_{m+1}, g_{m+2}, \dots, g_{m+n}$ and loose garment $g_{m+n+1}, g_{m+n+2}, \dots, g_{m+n+s}$. Fit garments were labeled “1”, tight garments were labeled “2” and loose garments were labeled “3”. We used the data comprised of “1”, “2” and “3” as output learning data to train the proposed model.

Figure 2. Output learning data collection.

2.3 Model Relation Between Digital Clothing Pressures and Garment Fit Condition

The concepts and data involved in this study are formalized as follows:

Let n be a number of nodes in input layers;

Let l be a number of nodes in hidden layers;

Let m be a number of nodes in output layers;

Let w_{ij} be a linked weight between input layer and hidden layer;

Let w_{jp} be a linked weight between hidden layer and output layer;

Let H_j be a set of hidden layer's output vector;

Let O_p be a set of output layer's output vector;

Let X_i be a set of input layer's input vector, where, it refers to digital clothing pressures of garment i , which are measured by virtual try-on software;

Let Y_p be a set of output layer's desired output vector, where, it refers to m garment fit levels, which are measured by real try-on, such as, fit, loose, tight;

Let a_j be a set of hidden layer's threshold;

Let b_p be a set of output layer's threshold;

Let e_p be a set of networks prediction errors;

Let η be the learning rate;

Let $f(\cdot)$ be the hidden layer's activation function.

As shown Figure 3, Back Propagation Artificial Neural Networks (BP-ANNs) is applied to model the relationship between digital clothing pressures and garment fit. The model learning with the BP-ANNs is composed of the following seven steps.

Step 1 Networks initialization. Determining input layer node number n , hidden layer node number l , and output layer node number m according to input and output (X_i, Y_i) . Initializing the hidden layer threshold a_j and output layer threshold b_p . Given learning rate η and neuron activation function $f(\cdot)$.

Step 2 Hidden layer output calculation. Calculating the hidden layer output H_j according to input layer's input vector X_i , input layer and hidden layers linked weights w_{ij} and hidden layer's threshold a_j .

$$H_i = f\left(\sum_{i=1}^n w_{ij} x_i - a_j\right), \quad j = 1, 2, \dots, l \quad (5-1)$$

Step 3 Output layer output calculation. Calculating BP-ANNs prediction output O_p according to hidden layer output H_j , hidden and output layers linked weights w_{jp} and output layer's threshold b_p .

$$O_p = \sum_{j=1}^l H_j w_{jp} - b_p, \quad p = 1, 2, \dots, m \quad (5-2)$$

Step 4 Error calculation. Calculating networks prediction error e_p according to output layer's prediction output O_p and output layer's desired output Y_p .

$$e_p = Y_p - O_p, \quad p = 1, 2, \dots, m \quad (5-3)$$

Step 5 Weight updating. Updating BP-ANNs connection weights w_{ij} and w_{jp} according to networks prediction error e_p .

$$w_{ij} = w_{ij} + \eta H_j (1 - H_j) x(i) \sum_{p=1}^m e_p w_{jp}, \quad i = 1, 2, \dots, n; j = 1, 2, \dots, l \quad (5-4)$$

$$w_{jp} = w_{jp} + \eta H_j e_p, \quad j = 1, 2, \dots, l; p = 1, 2, \dots, m \quad (5-5)$$

Step 6 Threshold updating. Updating BP-ANNs node threshold a_j and b_p according to networks prediction error e_p .

$$a_j = a_j + \eta H_j (1 - H_j) \sum_{k=1}^m e_p w_{kp}, \quad j = 1, 2, \dots, l \quad (5-6)$$

$$b_p = b_p + e_p, \quad p = 1, 2, \dots, m \quad (5-7)$$

Step 7 Testing whether algorithm iteration is over. If the error meets the presupposed precision or learning times are greater than the predefined maximum, then the algorithm is stopped. Otherwise, inputting next learning sample and the corresponding output expected values; then returning to step 2 and into the next round learning.

Using the steps above, we construct a garment fit evaluation model based on BP-ANNs. The input items of the proposed model are digital clothing pressures and the output items of that are garment fit conditions (fit, loose, and tight). Through learning from experimental data collected by real and virtual try-on, the proposed model can automatically predict garment fit without any real try-on.

Figure 3. Structure of Back Propagation Artificial Neural Networks (BP-ANNs).

3.0 Validation

In section II, we used neural networks to construct an intelligent model of garment fit evaluation. In this section, we introduce how to validate the model's prediction accuracy.

3.1 Bp-Anns Parameters Setting, Training and Prediction

Networks layer setting: It has been proved that any continuous function can be uniformly approximated by a BP networks model with only one hidden layer [37]. As our problem is rather simple (20 inputs, 1 output and nonlinear continuous relationship), the BP-ANNs with three layers is adapted to modeling of the relation between digital clothing pressures and garment fit.

Input and output layer nodes selections: The input layer is the link between the external signal and the BP neural networks. The number of its nodes depends on the dimensions of the learning input data. The number of nodes at the output layer varies with application. If the networks act as a classifier, the number of nodes at the output layer equals the number of predefined classes or categories. In our research, the nodes at the input layer are the k digital clothing pressures while the output is the unidimensional garment fit level.

Hidden layer setting: The number of neurons at the hidden layer has a significant effect on the BP-ANNs prediction accuracy. If this number is too small, the ability of learning from data in the networks will be decreased, leading to the convergence to a local optimum. If this number is too large, the phenomenon of over-fitting will occur, leading to a longer time of learning and arbitrary errors. Up to now, no systematic rules or equations exist allowing calculation of the optimal number of hidden neurons

[37]. In general applications, this number is selected by trial and error. In our study, the number of neurons in the hidden layer is determined using a frequently used empirical formula. Its value is 10.

Learning rate: Learning rate has an important effect on the performance of the BP neural networks. If it is too small, the number of training iterations will be increased and more time will be needed. If it is too large, the networks can learn quickly, but easily lead to a wrong convergence. After a number of tests on the BP learning algorithm with different values, I finally set the learning rate to 0.03 and the number of training iterations to 500.

BP-ANNs training [38]: Actually, BP-ANNs training process is a process for the connection weights adjustment. It mainly contains the following nine stages. 1) Initialize of the connection weights of the networks ; 2) Select a sample from the training dataset as the input of the networks ; 3) Calculate the output value of the networks ; 4) Calculate the error of the networks output related to the real value; 5) Adjust the connection weights by using the feedback from the output layer to the input layer; 6) Repeat Steps 3), 4) and 5) until the error is acceptable; 7) Select another sample of the training set data and repeat the above steps until the convergence of the algorithm.

BP-ANNs prediction: After identifying the connection weights by the previous training step, the proposed model in Figure 3 can be used to predict garment fit level by inputting the measured digital clothing pressures of a new garment.

3.2 Learning Data Collection and Garment Fit Evaluation Model Training

According to the method of input learning data collection (Experiment I), we used a measurement method, which were used in our previous researches [14, 15], to acquire digital clothing pressures. As shown in Figure 4, firstly, measuring points $F_1, F_2, \dots, F_{15}$ and $B_1, B_2, \dots, B_5$ were equally mapped on front and back pieces of the pants' patterns respectively (Note: the 'parts below knee have little effect on clothing fit; therefore, we did not map measuring points on these parts); secondly, we used CLO 3D Modelist software to try the patterns on a parametric human model, whose body dimensions were equal to the real body dimensions; finally, we measured digital clothing pressures of 72 pairs of pants according to the 20 predefined points. The collected data of digital clothing pressures was as the input learning and test data used for model construction and validation.

According to the method of output learning data collection (Experiment II), 72 pairs of pants were evaluated by real try-on. We defined fit, tight and loosed as follows: If a wearer feels neither tight nor loose in each part of a garment, the garment is considered fit for the wearer; If a wearer feels tight in one place of a garment; the garment is considered tight for the wearer; If a wearer feels loose in one place of a garment, the garment is considered loose for the wearer. We labeled fit garments with "1", tight garments with "2" and loose garments with "3". The data containing "1", "2"

and “3” was as the output learning and test data to construct and validate our proposed model.

Figure 4. Measurement method of digital clothing pressures by virtual try-on.

Table 1. Digital clothing pressures data collected by virtual try-on (input learning and test data) and garment fit condition data collected by real try-on (output learning and test data).

Data name	SNN	Fit Level	Digital clothing pressures (unit: virtual Kpa).			
			$F1$	$F2$	...	$B5$
PD	1	1	6.70	10.25	...	13.71
	2	1	3.75	6.49	...	2.72
	⋮	⋮	⋮	⋮	⋮	⋮
	23	1	8.26	11.51	...	7.43
	24	2	12.40	17.45	...	9.32
	25	2	19.81	28.33	...	16.21
	⋮	⋮	⋮	⋮	⋮	⋮
	47	2	17.2	22.37	...	12.74
	48	3	6.92	9.57	...	1.67
	49	3	14.59	16.56	...	0.58
p_{loose}	⋮	⋮	⋮	⋮	⋮	⋮
	72	3	7.58	9.12	...	0.47

Note: PD is Pressure Data; SSN is sample sequence number; F_1 , F_2 , F_3 , F_4 , ..., B_5 are measuring points of digital clothing pressures, please see Figure 4 (a).

Finally, the input and output data were combined together. As shown in Table 1, all the fit pants and their corresponding digital clothing pressures were integrated into

a data p_{fit} ; all the tight pants and their corresponding digital clothing pressures were integrated into a data p_{tight} ; and all the loose pants and their corresponding digital clothing pressures were integrated into a data p_{loose} . Data p_{fit} , p_{tight} and p_{loose} were divided into two parts. One part was use for model learning and the other part was used for the validation of model prediction accuracy.

Several surveys have shown consumer dissatisfaction with garment fit recorded to be more than 50% [6, 39]. Often, garment fit is already evaluated before the garment is sold. This information above indicates that the evaluation accuracy of traditional garment fit evaluation methods is obviously lower 50%. To compare with other data learning algorithms, we also calculated the prediction accuracy of garment fit evaluation based on other data learning algorithms, random forest, Bayesian classifier, discriminant analysis, etc. Because random forest has the merit of non-aggravating the overfitting of data as the number of trees increases [40]. As the number of the training sample is less, it is necessary to do a comparison with other algorithms for avoiding over-fitting phenomenon.

3.3 Garment Fit Evaluation Model's Prediction Accuracy Calculation

The validation flowchart is shown in Figure 5. The data collected in Experiment I and II were divided into training data and testing data. Firstly, we used the training data to train our proposed BP-ANNs based fit evaluation model. That is to adjust the weights of neural networks. After learning from training data, the test data is used for validating the model's prediction accuracy.

Figure 5. The flow chart of model's prediction accuracy validation.

In order to obtain more reasonable validation result, we use the K-fold cross-validation to test the approach by calculating the prediction accuracies of the proposed models. The principle of K-fold cross validation is introduced as follows. The data set is divided into k subsets, and the holdout method is repeated k times. Each time, one of the k subsets is used as the test set and the other $k-1$ subsets are

put together to form a training set. Then the average error across all k trials is computed. The advantage of this method is that it matters less how the data gets divided. Every data point gets to be in a test set exactly once, and gets to be in a training set $k-1$ times. The variance of the resulting estimate is reduced as k is increased.

The test results of K-fold cross validation show that the prediction accuracies of BP-ANNs-based garment fit evaluation method is the highest, followed by Random Forest, Bayesian Classifier, and the worst is Discriminant Analysis. Specially, the prediction accuracies of machine-learning-based garment fit evaluation methods are all significantly higher than that of traditional method by real try-on (**Error! Reference source not found.**). This indicates that data-learning-based garment fit evaluation methods is better than traditional method.

Table 2. Comparison of prediction accuracy between BP-ANNs, random forest and traditional fit evaluation method by real try-on.

Prediction methods	Prediction Accuracy
Fit evaluation method based on BP-ANNs	93%
Fit evaluation method based on Random Forest	83%
Fit evaluation method based on Bayesian Classifier	81%
Fit evaluation method based on Discriminant Analysis	78%
Traditional fit evaluation method by real try-on	Less than 50%

Note: In the training process, the number of the hidden layer nodes is 10, and the number of trees of the Random Forest is 50. Prediction Accuracy is the average of 10 K-fold cross validations (K=10).

4.0 Application

Figure 6. Garment fit prediction for manufacturing.

Fit evaluation is an important link in clothing product development and sales. In this section, we gave an application to evaluate garment fit using our proposed method for garment e-shopping. As shown in Figure 6, a customer chooses a garment in a garment online shopping store; according to the customer's body dimensions, we adjust the 3D parametric mannequin; then we find the selected garment's patterns from pattern databased, and try the patterns on the adjusted 3D parametric mannequin; next, we measure digital clothing pressures and input the pressures into our proposed model; the model predicts garment fit automatically finally. If the customer satisfies with the garment fit condition predicted by our proposed method, we recommend the customer to buy it. Otherwise, we change a new size to predict its fit until the customer satisfy.

5.0 Discussion

The traditional garment fit evaluation methods require customers having a real try-on; it leads to high garment manufacturing costs. Therefore, we proposed a data-learning-based method to predict garment fit. In this model, the digital clothing pressure data collected by virtual try and garment fit condition data collected by real try-on have mapping relationships. Even though some differences between virtual and real clothing pressures exist, the reliability of the proposed model is unaffected. The main contributing factor on the reliability of the proposed model is the outputting data collected by real try-on. Therefore, real try-on is very important for output data collection. As the proposed model learns from the experimental data collected by real try-on, the prediction accuracy is reliable.

In our previous studies, we used Bayesian classifiers to predict garment fit [1]. The garment fits were divided into fit and unfit. However, the two fit levels are too simplified. Clothes that are too loose or too tight can lead to unfit. In order to evaluate fit more accurately, we divided garment fit into three levels: fit, tight and loose in this research. Although, our proposed method is better than traditional method by real try-on to evaluate garment fit. There are still some shortcomings needed to improve. For example, the overall feel of a garment is loose, but some parts may be tight or fit; for the same reason, the overall feel of a garment is tight, but some parts may be loose or fit. Due to the current classification of garment fit condition is still simple, garment fit conditions can be divided into more categories in the future research, such as waist part's fit condition, hip part's fit condition, crotch part's fit condition. For garment e-shopping, our proposed method requires customers providing their body dimensions. With the advent of 3D body scanner, body dimensions can be measured automatically and rapidly using this device. The 3D body scanner can not only measure body dimensions, but also acquire human body's point cloud data. 3D human model constructed based on the point cloud is more accurate than body dimensions. Therefore, combining 3D body scanning technology, the fit evaluation methods based on data learning technology could predict garment fit more accurately.

Although our method has many advantages, it also has some shortcomings. One of the biggest limitations of our proposed method is that, for another type of garment, the proposed model should be re-trained.

6.0 Conclusion

In this paper, we proposed a data-learning-based garment fitting prediction model. The result indicates that data-learning-based garment fit evaluation methods are much better than traditional method by real try-on. Compared with traditional garment fit evaluation methods, the advantage of our approach is: 1) It excludes physical participation of customers; 2) The prediction accuracy of BP-ANNs-based garment fit evaluation method is not only better than that of Random Forest, Bayesian Classifier, Discriminant Analysis based methods, but also significantly higher than that of traditional method'; 3) It is not only suitable for garment e-shopping, but also for garment products development.

In practice, the greatest contribution of our method is to realize automatic and intelligent garment fit evaluation. Our proposed method can significantly reduce the number of sample-making and real try-on in the process of apparel product development, thereby reducing the cost of apparel product development. Further research can be conducted from two aspects: 1) Validating the prediction accuracy of the proposed method under the condition of increasing the number of garment fit conditions; 2) Combining 3D body scanning technology, to extend application range of the data-learning-based garment fit evaluation.

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Data availability

All data generated or analyzed during this study are included in this published article.

Code availability

Not applicable.

Ethics approval and consent to participate

Not applicable.

Consent to participate

All authors have read and agreed to participate.

Consent for publication

All authors have read and agreed to publish the manuscript.

Competing interests

The authors declare no competing interests.

Author contributions

All authors contribute equally.

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