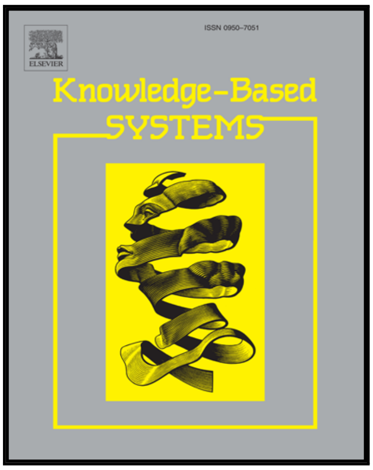
Accepted Manuscript



Fit evaluation of virtual garment try-on by learning from digital pressure data

Kaixuan Liu , Xianyi Zeng , Pascal Bruniaux , Jianping Wang , Edwin Kamalha , Xuyuan Tao

PII: S0950-7051(17)30323-4
DOI: 10.1016/j.knosys.2017.07.007
Reference: KNOSYS 3971

To appear in: *Knowledge-Based Systems*

Received date: 25 March 2016
Revised date: 29 June 2017
Accepted date: 2 July 2017

Please cite this article as: Kaixuan Liu , Xianyi Zeng , Pascal Bruniaux , Jianping Wang , Edwin Kamalha , Xuyuan Tao , Fit evaluation of virtual garment try-on by learning from digital pressure data, *Knowledge-Based Systems* (2017), doi: 10.1016/j.knosys.2017.07.007

Highlights:

- A remote garment fit evaluation model using machine-learning technique is proposed to estimate garment fit without any real try-on.
- Digital clothing pressures, generated from a 3D garment CAD software, were taken into account during the remote garment fit evaluation.
- Our proposed model has significance in garment e-shopping

Fit evaluation of virtual garment try-on by learning from digital pressure data

Kaixuan Liu[a,b,c,d*], Xianyi Zeng[c,d], Pascal Bruniaux[c,d], Jianping Wang[b], Edwin Kamalha[c,d], Xuyuan Tao[c,d]

[a] Apparel and Art Design College, Xi`an Polytechnic University, Xi`an 710048, China

[b] College of fashion and design, Donghua University, Shanghai 200051, China

[c] University of Lille 1, Nord de France, 59000 Lille, France

[d] GEMTEX Laboratory, ENSAIT, 59100 Roubaix, France

Abstract:

Presently, garment fit evaluation mainly focuses on real try-on, and rarely deals with virtual try-on. With the rapid development of E-commerce, there is a profound growth of garment purchases through the internet. In this context, fit evaluation of virtual garment try-on is vital in the clothing industry. In this paper, we propose a Naive Bayes-based model to evaluate garment fit. The inputs of the proposed model are digital clothing pressures of different body parts, generated from a 3D garment CAD software; while the output is the predicted result of garment fit (fit or unfit). To construct and train the proposed model, data on digital clothing pressures and garment real fit was collected for input and output learning data respectively. By learning from these data, our proposed model can predict garment fit rapidly and automatically without any real try-on; therefore, it can be applied to remote garment fit evaluation in the context of e-shopping. Finally, the effectiveness of our proposed method was validated using a set of test samples. Test results showed that digital clothing pressure is a better index than ease allowance to evaluate garment fit, and machine learning-based garment fit evaluation methods have higher prediction accuracies.

Keywords:

digital clothing pressure, support vector machines, Naive Bayes, active learning, ease allowance, real try-on

1. Introduction

Today garment e-shopping has become more prominent worldwide [1]. However, an important technical barrier that garments displayed online cannot be physically evaluated for fitting effects on a specific consumer [2]. Thus, virtual try-on technology was developed to evaluate garment fit [2, 3], finding wide application in the clothing industry in the last ten years. A number of virtual try-on programs, such as *Clo 3D*, *Lectra 3D Prototype*, *OptiTex* and *V-Stitcher 3D*, are available on the

* Corresponding author: Kaixuan Liu
E-mail addresses: L40260611@hotmail.com

market for garment fit evaluation [4]. These 3D virtual try-on software systems follow similar principles, i.e. showing virtual garment static and dynamic performance from identified human morphological and fabric properties and their interactions. Defining this performance involves the use of complex mechanical and geometric modeling and simulation techniques, such as finite elements [5]. The software, normally include four main modules [4]: 1) a 3D parametric mannequin module, 2) a fabric properties module, and 3) a virtual pattern sewing module. To model the human body rapidly, the 3D parametric mannequin module is used to construct a personalized 3D human model from measurement of a 3D body scanner or a measuring tape, related to a specific customer. Several key body dimensions, such as height, waist circumference, and hip circumference [6], control the parametric mannequin's dimensions. By adjusting key body dimensions, the 3D parametric mannequin module can create various body shapes and dimensions rapidly and automatically, meeting customers' body shapes and dimensions. Then, the fabric properties module, usually based on a mechanical model, will permit the simulation of different perceived properties (draping, texture, elasticity, bending, etc.) of a virtual fabric through adjustable fabric technical parameters. Finally, the virtual pattern-sewing module assembles the predefined garment patterns on the specific 3D human body and sews the patterns together, taking into account the performance of the simulated fabric. The combination of these three modules constitutes a virtual try-on system, permitting the simulation of the real garment making process. In a virtual 3D try-on process, consumers and designers can visualize the static and dynamic performance of the selected fabrics and garment fit effects in terms of comfort, expressed by simulated pressures between the human body and fabrics, and fashion styles.

Through virtual try-on, consumers can easily decide whether they like a garment style or not. However, these virtual try-on applications, are strongly dependent on mathematical models used in the software [5], and cannot give full accurate garment fit evaluation. Moreover, for real try-on, the wearer can feel whether a garment fits; unlike, with virtual try-on [7]. The issue of garment fit evaluation is a research hotspot and a great challenge [8]. In practice, no matter how beautiful a garment is, and how excellent the fabric's properties are, a customer will not select it if it is unfit [8]. Garment fit is a major factor affecting customers' purchasing decisions [9, 10]. For garment e-shopping, consumers cannot physically try on garments; therefore, estimating the garment fit without real try-on is still an issue for researchers.

Lately, there are mainly two methods to evaluate garment fit through virtual try-on. One approach is that the visual evaluation is carried out on a 3D garment by expert fashion designers [11-13]. Obviously, this subjective visual evaluation is neither accurate nor convincing. The other approach is to measure the ease allowances, which is the dimensional difference between human body and garment in the girth direction [14]. Then, expert fashion designers analyze these measured ease allowances based on their own empirical knowledge to evaluate garment fit. However, the ease allowance can reflect the fitting feeling when neither 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, the fitting effects could be different if the fabrics are different. Evidently, ease allowance only is not enough for characterizing the fitting effects of a garment try-on. Moreover, these two approaches to garment fit need empirical knowledge. Often, the predicted results are entirely dependent on the subjectivity of designers, such as experience and personal preference, which erodes their accuracy. Therefore, people without fashion design knowledge cannot easily use the traditional fit evaluation methods of virtual garments. For shopping online, there are thousands of garments purchased in a short time. If every garment fit is evaluated using traditional methods, the work is so enormous. Therefore, it is necessary to find a method that can evaluate garment fit automatically, rapidly and accurately. In this context, we proposed a machine learning-based model to evaluate garment fit. The input item of the proposed model is an indicator reflecting the garment fit condition, whose output is fit or unfit. Compared to traditional garment fit evaluation methods, the greatest advantage of our proposed method is that it can predict garment fit rapidly and automatically, without any real try-on and designers' involvement.

Modeling by learning from experimental data has been widely used in the clothing industry [15, 16], including evaluation of garment and fabric products [12, 17-19], evaluation of wear comfort [20], garment CAD systems [21-24], clothing manufacturing [25-30]; clothing retailing [31-36], and apparel supply chain management [37, 38]. However, few studies have focused on fit evaluation of virtual try-on using machine learning. In order to increase the accuracy of fit evaluation using 3D virtual body shapes and virtual garments, we introduce a data machine learning-based model. This method requires inputting an indicator that can reflect garment fit and returning an output as the predicted result of garment fit. In the preceding sections, we have discussed and indicated that the ease allowance between a garment and the human body is not a good indicator of reflecting garment fit. We, therefore, opted to find a more suitable indicator. The influence of fabric properties can be measured using the digital clothing pressures, distributed over the human body of the wearer and provided by a 3D garment CAD software like *CLO 3D* [39-41]. It is for this reason that, in our study, we selected digital clothing pressures as a key indicator for remote garment fit prediction. In practice, the digital pressure-based method will be more efficient for fit evaluation than ease allowance-based methods, which are more adapted to loose garments.

Bayes classifiers have been applied successfully in a wide variety of domains [42]. Their representations are quite intuitive and easy to understand [43]. The advantages of Naive Bayes are: 1) A Naive Bayes model has a solid mathematical foundation, as well as the stability of the classification efficiency. 2) The number of estimated parameters for modeling with Naive Bayes is relatively fewer, the model is less sensitive to missing data, and the algorithm is relatively simpler. 3) A Naive Bayes model has very high classification accuracy in many practical cases. Due to these advantages, Naive Bayes is applied to model the relationship between digital clothing pressures and garment fit level. The inputs of the proposed model are digital clothing pressures on different body parts, while the output is the fit evaluation result (fit or unfit). By learning from a number of experimental data measured on a number of samples, we set up the model, capable of quickly estimating the fit for a new garment without any real try-on. Our proposed model can be used to help consumers in realizing online efficient garment shopping.

The following sections are organized as follows. Section 2 introduces the general scheme and data formalization. Sections 3 presents the collection of input and output learning data respectively. Section 4 expounds the construction of garment fit prediction model. In Section 5, we evaluate the accuracy of the proposed model and give a practical application of the proposed model. In Section 6, we discuss the application prospect, limitation, etc. Finally, we present some conclusions and possible further works in section 7.

2. General principle and formalization

2.1 General principle

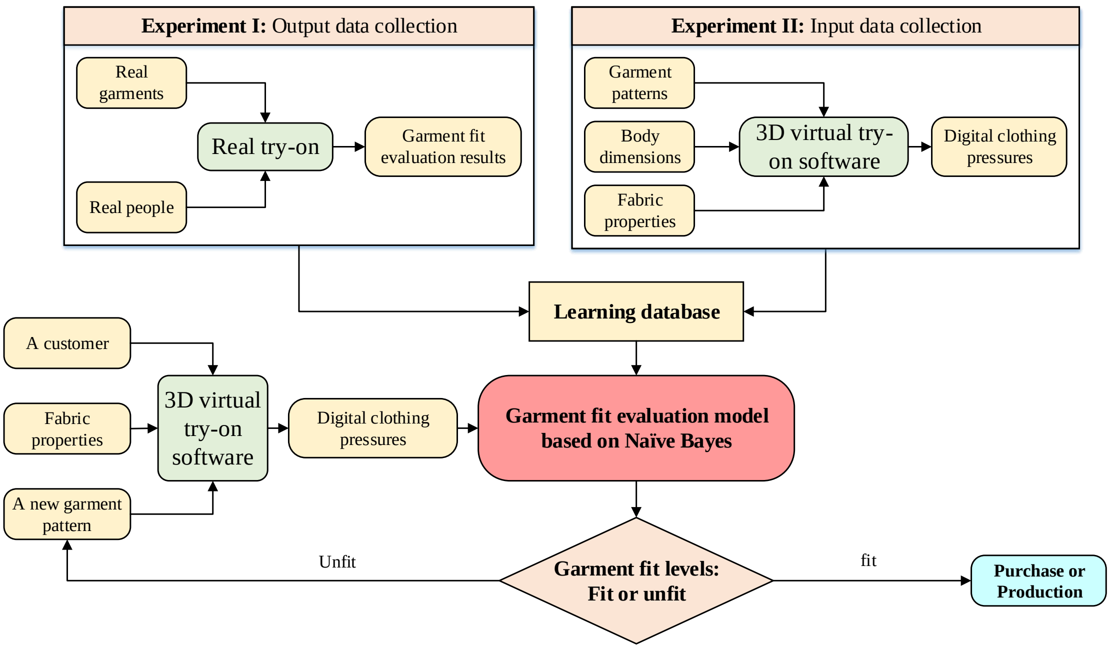


Fig. 1 General scheme of MLBGFET.

The general scheme of the mentioned garment fit evaluation model is described in Fig. 1.

First, Experiment I is aimed at collecting the output learning data. Nine subjects try on 72 pairs of pants respectively. They divide all the pants into fit pants and unfit pants.

Second, Experiment II is aimed at collecting the input learning data. We measured digital clothing pressures of the 72 pairs of pants respectively by virtual try-on technology.

Next, garment fit evaluation model based on Naive Bayes and Support Vector Machines (SVMs) is trained by the input and output learning data.

Finally, the proposed model predicts garment fit without any real try-on after learning from the collected data.

2.2 Formalization of the concepts and data

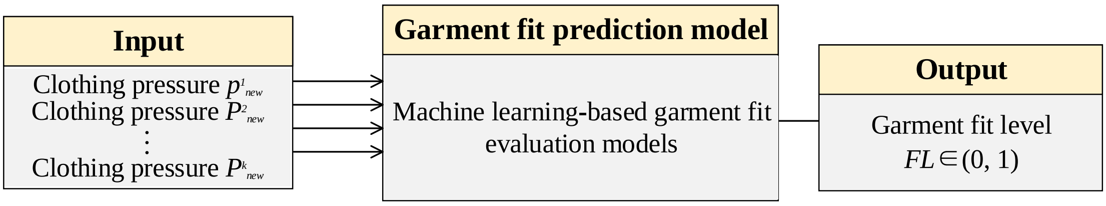


Fig. 2 Modeling the relation between digital clothing pressures and garment fit

As shown in Fig. 2, we built a machine learning-based garment fit evaluation model, the input of which are digital clothing pressures and the output of which is garment fit level. The data and concepts involved in this study are formalized as follows:

Let FL be the fit level of a garment, i.e. 1-fit, 0-unfit.

Let $G = \{g_1, g_2, \ldots, g_m\}$ be a set of m real garments used in our study.

Let $P_i = \left(p_i^1, \ldots, p_i^j, \ldots, p_i^k\right)$ be a vector of digital clothing pressures obtained during the virtual try-on of the garment g_i where p_i^j is the pressure on the key position j of the garment g_i (we suppose that there exist k key positions on the whole garment surface). In a general case, the vector of digital pressures $\mathrm{P}_{new} = \left(p_{new}^1, \ldots, p_{new}^j, \ldots, p_{new}^k\right)$ of a new garment g, is taken as input variables of the model.

3. Learning data acquisition

3.1 Preparation work for experiments

We design Experiments I and II to collect data. Experiment I aims to acquire output learning data on garment fit by using real try-on; Experiment II aims to acquire input learning data on digital clothing pressures by using virtual try-on. Anthropometric equipment, software, subjects, garments, fabrics, etc. involved in Experiment I and II are expounded below respectively.

***Anthropometric equipment*:** The Vitus Smart 3D body scanner is applied to collect human body dimensions for virtual try-on. This device captures body measurements with a $\pm 1\, mm$ level of accuracy, in accordance with the international standard DIN EN ISO 20685.

***Software*:** The software CLO 3D is applied to measure digital clothing pressures. This software permits to create virtual, close-to-life garment visualization with cutting-edge simulation technologies. Virtual fabrics available in CLO 3D are based on actual fabrics commonly used in the industry and they currently have a 95% accuracy rate [44].

***Subjects*:** Nine female subjects with representative body shapes are selected for performing real try-on and body dimension measurement. According to China National Standard (GBT 1335.2-2008), their body dimensions (155/60A, 155/62A, 160/64A, 160/66A, 160/68A, 165/70A, 165/72A, 170/74A and 170/76A) can account for the total female population of China [45]. The corresponding 3D virtual body models used for virtual try-on are shown in Fig. 3. (Note: In China, female body shapes are classified in four categories (Y, A, B, C) according to the difference of bust-waist. The body shape belongs to the type Y if this value is located in the range of 19-24 cm, the type A for the range of 14-18 cm, the type B for the range of 9-13 cm, and the type C for the range of 4-8 cm. 155/60A means that the body type is A, the stature 155 cm and the waist 71 cm).

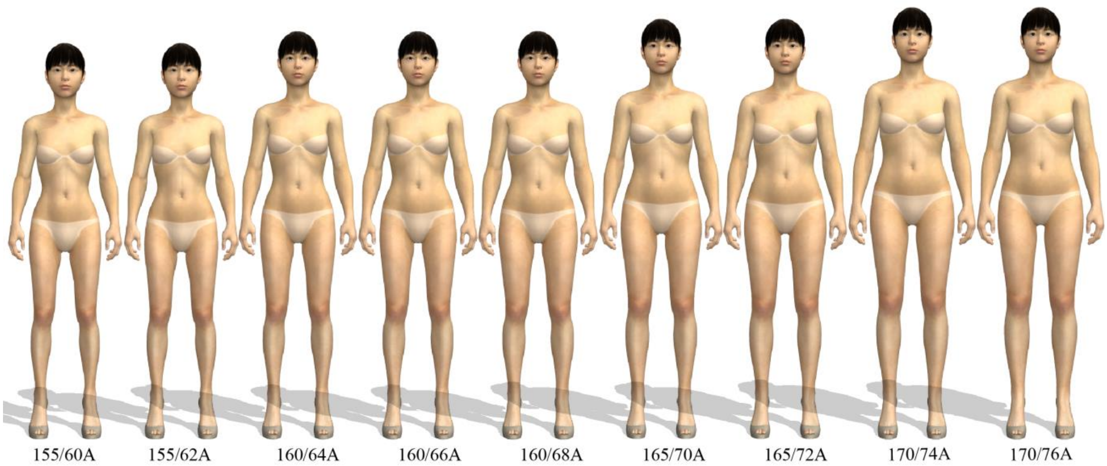


Fig. 3 Nine virtual bodies used for virtual try-on generated based on the nine subjects.

Garments: 72 pairs of straight pants, which cover most of pants' sizes, are involved in the real try-on experiments for data collection (Table 1). We select the pant type to test our proposed method because that they are the most challenging clothing item for a good fit [2]. If the proposed model predicts pants' fit accurately, this method could be also available for other styles.

Table 1

Waist girths, hip girths of 72 pairs of pants used in the experiments (unit: cm)

60.0/75.5	62.5/ 78.0	65.0/80.5	67.5/83.0	70.0/85.5	72.5/88.0	75.0/90.5	77.5/93.0	80.0/95.5
60.0/78.0	62.5/ 80.5	65.0/83.0	67.5/85.5	70.0/88.0	72.5/90.5	75.0/93.0	77.5/95.5	80.0/98.0

60.0/80.5	62.5/ 83.0	65.0/85.5	67.5/88.0	70.0/90.5	72.5/93.0	75.0/95.5	77.5/98.0	80.0/100.5
60.0/83.0	62.5/ 85.5	65.0/88.0	67.5/90.5	70.0/93.0	72.5/95.5	75.0/98.0	77.5/100.5	80.0/103.0
60.0/85.5	62.5/ 88.0	65.0/90.5	67.5/93.0	70.0/95.5	72.5/98.0	75.0/100.5	77.5/103.0	80.0/105.5
60.0/88.0	62.5/ 90.5	65.0/93.0	67.5/95.5	70.0/98.0	72.5/100.5	75.0/103.0	77.5/105.5	80.0/108.0
60.0/90.5	62.5/ 93.0	65.0/95.5	67.5/98.0	70.0/100.5	72.5/103.0	75.0/105.5	77.5/108.0	80.0/110.5
60.0/93.0	62.5/ 95.5	65.0/98.0	67.5/100.5	70.0/103.0	72.5/105.5	75.0/108.0	77.5/110.5	80.0/113.0

Note: 60/67.5 means that the garment's waist girth is 60 cm, whose hip girth is 75.5 cm; 60/78.0 means that the garment's waist girth is 60 cm, whose hip girth is 78.0 cm; and so on.

Fabric: Fabric physical properties influence digital clothing pressures significantly. Therefore, they should be considered in the virtual try-on experiment. However, these fabric properties, as well as garment styles, have already been taken into account in the digital clothing pressures measured in the 3D garment CAD environment. Therefore, we do not need to specially study the effects of fabric properties on garment fit. In Experiment II, we just selected a frequently used jeans fabric with the mechanical properties shown in Table 2 for making different garments of virtual try-on.

Table 2
Values of the fabric mechanical properties

Abbr.	BST	BSP	BRT	BRP	ST	SW	BT	BP	SH	DE	ID	FC
Value	30	30	50	50	32	32	35	35	23	35	1	3

Note: BST is buckling stiffness-weft; BSP is buckling stiffness-warp; BRT is buckling ratio-weft; BRP is buckling ratio-warp; ST is stretch-weft; SW is stretch-warp; BT is bending-weft; BP is bending-warp; SH is shear; DE is density; ID is internal damping; FC is friction coefficient. The fabric mechanical properties are relative values in the range [1-99], defined by the software.

Garment fit level: In this research, we classify all garment fit values into two levels fit or unfit. These fit levels are used in both real and virtual garment try-on.

Try on condition: Before each real try-on evaluation, each subject wears a piece of underwear that is thin and neither tight nor loose. The try-on experiment is carried out indoor under a temperature of 18-20 °C。

3.2 Experiment I: Acquisition of the data on garment fit

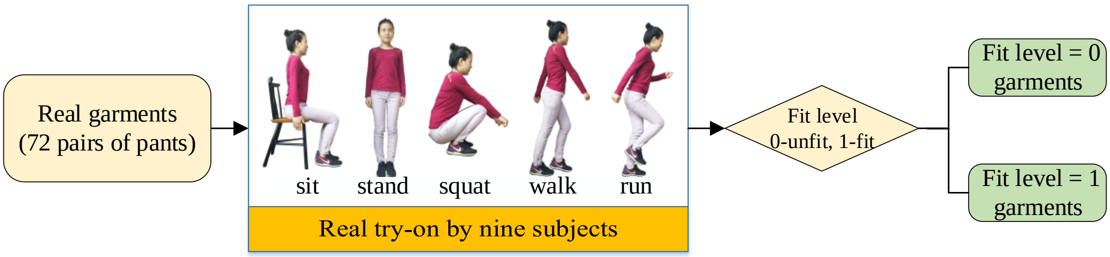


Fig. 4 Garment fit data collection by real try on (Output learning data).

Table 3
Size distribution of 72 pairs of pants selected by the nine subjects

155/60A	155/62A	160/64A	160/66A	160/68A	165/70A	165/72A	170/74A	170/76A
60.0/78.0	62.5/ 78.0	60.0/75.5	60.0/80.5	60/83.0	67.5/95.5	70.0/85.5	72.5/105.5	72.5/93.0
60.0/88.0	62.5/ 83.0	60.0/85.5	65.0/80.5	62.5/ 85.5	70.0/93.0	70.0/100.5	75.0/90.5	77.5/100.5
62.5/ 80.5	60.0/90.5	62.5/ 90.5	67.5/85.5	65.0/98.0	72.5/95.5	72.5/88.0	75.0/103.0	77.5/105.5
62.5/ 88.0	60.0/93.0	62.5/ 95.5	70.0/95.5	65.0/93.0	72.5/98.0	72.5/90.5	75.0/105.5	77.5/110.5
62.5/ 93.0	65.0/88.0	65.0/90.5	70.0/98.0	67.5/83.0	75.0/95.5	75.0/108.0	77.5/93.0	80.0/105.5
65.0/83.0	67.5/90.5	65.0/85.5	72.5/100.5	67.5/100.5	75.0/98.0	77.5/103.0	77.5/95.5	80.0/108.0
65.0/95.5	67.5/98.0	67.5/93.0	75.0/93.0	70.0/88.0	77.5/98.0	80.0/95.5	80.0/100.5	80.0/110.5
67.5/88.0	70.0/103.0	72.5/103.0	75.0/100.5	70.0/90.5	77.5/108.0	80.0/98.0	80.0/103.0	80.0/113.0

Note: each column represents eight pairs of pants selected by one subject.

Table 4
Garment fitness data collected by real try-on (output learning data)

FL	Fit pants					Unfit pants				
	1	1		1	1	0	0	0	0	0
Sample No.	1	2	3	···	23	24	25	26	···	72

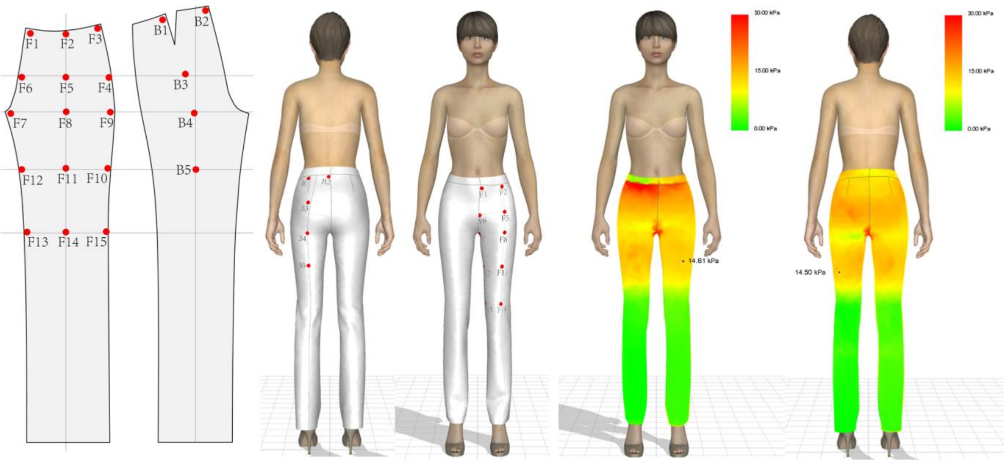
Experiment I is designed to evaluate garment fit levels using the real try-on. 72 pairs of pants are made according to the sizes in Table 1. The experiment procedure is shown in Fig. 4. Nine selected female subjects with different body shapes (Fig. 3) participate in the garment fit evaluation procedure. The details are given below.

Step 1**:** Each of the nine subjects selects eight pants from the 72 pairs of real pants according to her personal preference, like what she usually does in a garment shop. One pair of pants is selected by only one subject. The selected results are shown in Table 3.

Step 2**:** Each subject realizes her try-on with the selected pants by performing a number of gestures: sitting down, standing, squatting, running and walking (See Fig. 4). After that, she gives an overall fit level of the evaluated pants using one of the two scores (fit or unfit).

Finally, the nine subjects evaluate the fit levels of all the 72 pairs of pants. According to these evaluation results, the 72 pairs of pants are classified into the set of fit pants (23 pairs) and the set of unfit pants (49 pairs) (see Table 4). The data will be taken as input learning data to build the proposed models.

3.3 Experiment II: Acquisition of the data on digital clothing pressures



(a) Measuring points (b) Virtual try-on (c) Measuring clothing pressure

Fig. 5 Digital clothing pressure measurement by virtual try-on (Input learning data).

We design Experiment II to measure the digital clothing pressures at the key positions of the garment surface using the *CLO 3D* software (Fig. 5). The concrete scheme of Experiment II is described as follows.

Step 1: We built nine 3D human models whose body dimensions are equal to those of the nine subjects (see Fig. 3).

Step 2: We determine key positions $F1$, $F2$, …, $F15$ and $B1$, $B2$, …, $B5$ of each pair of pants, which are uniformly distributed on the front piece pattern and on the back piece pattern respectively (Fig. 5(a)). As the parts below knee have little effect on clothing fit, we do not define any key positions on them.

Step 3: According to Table 3, we make virtual try-on with the patterns of the 72 pairs of pants on the 3D human models corresponding to the body dimensions of nine subjects previously selected (Fig. 5(b) and Fig. 3).

Step 4: We measure the digital clothing pressures of each pair of pants on predefined 20 key positions of each garment during its virtual try-on (Fig. 5 (c)).

The digital clothing pressure data of the 72 pairs of pants are shown in Table 5. The corresponding data (input data) will be combined with the data of garment fit evaluation, collected in Section 5.2.2 (output data), for building the fit prediction models in Fig. 2.

Table 5
Digital clothing pressures data collected by virtual try-on (input learning data)

Sample No.	Digital clothing pressures (unit: KPa).										
	$F1$	$F2$	$F3$	$F4$	$F5$	$F6$	$F7$	$F8$	$F9$	⋯	$B5$
1	6.92	9.57	12.34	3.22	4.35	5.66	7.82	4.35	3.19	⋯	1.67
2	6.58	8.98	14.74	3.12	6.03	6.35	7.39	5.41	2.64	⋯	1.15
3	7.58	9.12	8.12	1.78	5.37	7.30	13.33	4.95	1.69	⋯	0.47

4	10.62	13.12	12.80	3.02	5.95	5.23	9.76	5.39	3.68	⋯	1.15
5	10.01	4.65	13.47	3.08	5.54	8.68	10.87	5.06	3.65	⋯	0.33
6	9.27	11.53	12.31	3.29	6.10	7.23	7.92	5.46	2.59	⋯	0.21
7	5.05	7.05	14.47	2.83	4.77	5.86	10.32	4.44	2.37	⋯	0.94
8	13.31	11.80	30.57	2.43	4.23	8.86	23.15	4.37	1.24	⋯	0.50
9	4.83	8.92	10.85	2.38	4.11	6.19	11.18	4.72	2.67	⋯	1.02
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋯	
72	8.00	30.81	36.80	36.99	20.15	25.20	18.77	58.13	15.70	⋯	15.13

Note: The numbers of the samples are the same as those of Table 4; $F1$, $F2$,…, $B5$ refer to the key positions of the digital clothing pressures, see Fig. 5 (a).

4. Modeling the relation between clothing pressures and garment fit level

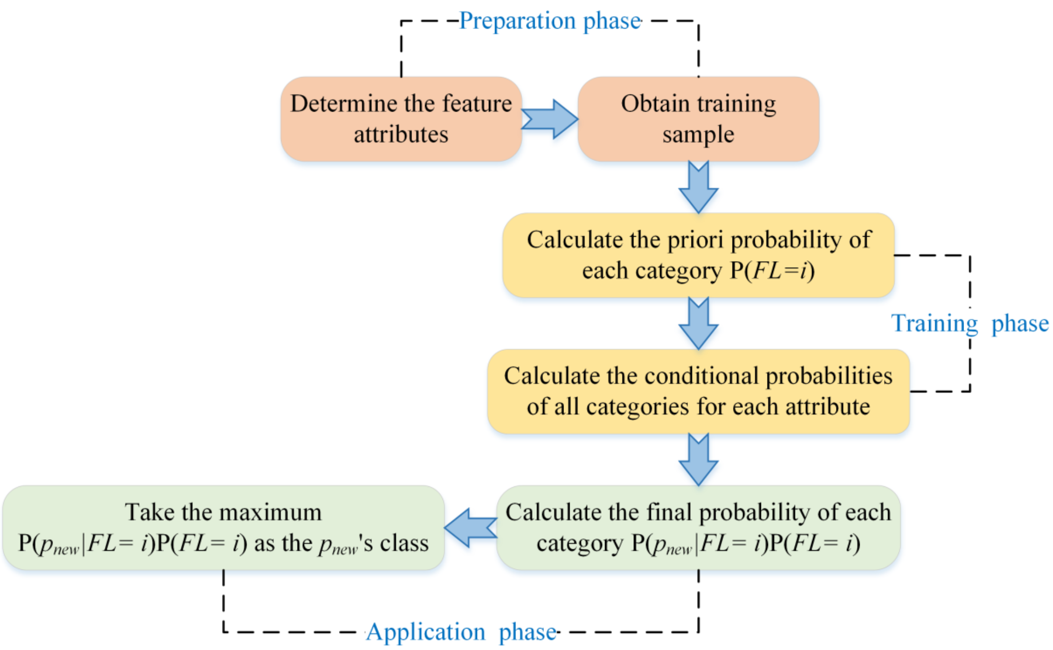


Fig. 6 Modeling with Naive Bayes.

As an effective tool for modeling with data learning, the Naive Bayes classifier is used in our approach for constructing the garment fit evaluation model. We present the specific modeling procedure in Fig. 6. It is composed of the following five steps:

Step 1*: *Determining the characteristics of attributes.

In the procedure of modeling, the digital clothing pressures measures on the k predefined key positions on the garment are taken as the characteristics attributes of the model. According to the general principle of Naive Bayes, we suppose that these k characteristics attributes are independent each other and all respect normal distributions.

Step 2*: *Acquiring training samples.

Two experiments I and II are carried out to collect training data by real and virtual try-on. The input and output training data are digital clothing pressures and garment fit levels respectively.

Step 3*: *Computing the prior probabilities of each category.

We have two levels of garment fit (categories). Thus, the prior probability of each category i ($i \in \{1, 0\}$) can be:

$$P(FL_i) = \frac{the\ number\ of\ fit\ evaluations\ corresponding\ to\ the\ i - th\ level}{the\ total\ number\ of\ fit\ evaluations}$$

Step 4*: *Computing the conditional probability of the new sample $\boldsymbol{P_{new}}$**.**

$$P(P_{new}|FL = i) = \prod_{j=1}^{k} P\left(p_{new}^{j}/FL = i\right) \ (i \in \{1, 0\})$$

$$P(FL = i|P_{new}) = \frac{P(FL = i)P(P_{new}|FL = i)}{\sum_{i=1}^{5} P(FL = i)P(P_{new}|FL = i)} \ (i \in \{1, 0\})$$

Step 5*: *Predicting with Naive Bayes classifier.

The classification rule of the Naive Bayes classifier is given below.

If $P(FL = l|P_{new}) = \max_{i=1\ or\ 0}\{P(FL = i|P_{new})\}, (l \in \{1,0\})$, then the new sample P_{new} corresponds to the fit level l.

5. Model validation

Table 6

Prediction accuracies calculated by the K-fold cross validation (k = 10)

Algorithms	Prediction accuracy	
	Digital clothing Pressures	Ease allowance
Naive Bayes	93.1%	76.4%
SVMs	84.7%	77.8%

In this section, we compare the performances of the proposed model. The input and output data for setting up the model are found in Table 4 and Table 5 respectively. As the number of learning data is very limited in this research, which may cause ‘‘over fitting’’ problem, leading to a very unstable performance of the model output, we apply K-fold cross validation approach to calculate the prediction accuracies of the proposed model. To compare with other machine learning algorithms, we also calculate the prediction accuracies of the SVMs-based and ease allowance-based garment fit evaluation models. According to the defination of ease allowance, the waist’s ease allowace equals to garment’s waist girth minus human body’s wiast girth ; the hip’s ease allowace equals to garment’s hip girth minus human body’s hip girth.

As shown in Table 6, the prediction accuracy of Naive Bayes model (93.1%) is better than that of SVMs model (84.7%) with selected digital clothing pressure as a fit evaluation index. The prediction accuracy of Naive Bayes model (76.4%) is slightly worse than that of SVMs model (77.8%) with selected ease allowance as a fit evaluation index.

6. Discussion

6.1 Influence of the difference between real and digital pressures on the prediction results

In the introduction, we have pointed out that the ease allowance between a garment and the human body is not a good indicator of reflecting garment fit. Therefore, we opted to find a more suitable indicator. The influence of fabric properties can be measured using the digital clothing pressures distributed on the garment surface covering the human body of the wearer. These digital clothing pressures are easily measured in a garment CAD software environment like CLO 3D. Our previous research shows that the digital clothing pressures can reflect garment wear comfort accurately [39]. It is for this reason that we select the digital clothing pressures as a key indicator for performing remote garment fit prediction without real try-on. The test result indicates the digital pressure-based methods are more efficient in fit evaluation than the ease allowance-based methods, which can be adapted to loose garments only instead of tight ones.

The proposed models enable to set up accurate and quantitative relations between digital clothing pressure data measured during a virtual try-on and garment fit data evaluated during a real try-on. For a new garment with an unknown fit level, we can measure its digital clothing pressures and then apply a previously proposed model for predicting its fit according to the measured digital clothing pressures. These models are significant and can accurately reflect comfort feeling of garments with different fabric mechanical properties because the digital and real clothing pressures not only have the same variation trends (i.e., the digital clothing pressure at a position is high when a subject feels tight at the same position, and vice versa.) [5, 39, 40, 46-48], but also are rather close each other in a certain range. As the learning and prediction of the proposed model are both based on digital clothing pressures and do not deal with any real clothing pressures, we do not need to precisely identify real clothing pressures. Even if there are some differences between digital and real clothing pressures, the prediction accuracies of the proposed models are not affected.

6.2 Application prospect

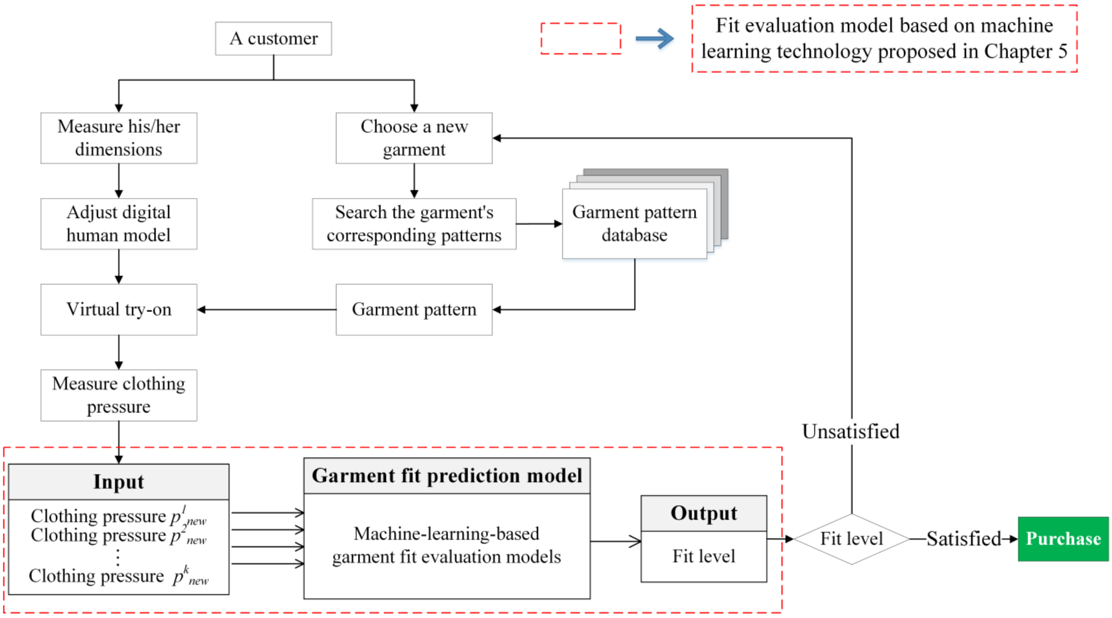


Fig. 7 Process 4: Remote garment fit prediction for online shopping.

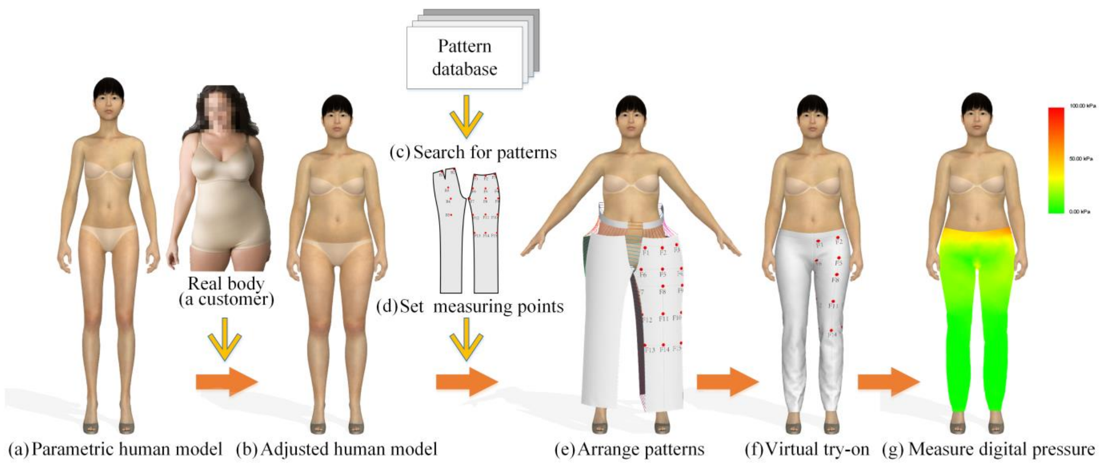


Fig. 8 3D human model adjustment and virtual try-on.

With increasing online sales, the fit of garments has serious implications for a fashion retailer because ill-fitting garments are directly related to product return rates [49, 50]. The evaluation of garment fit without the physical participation of customers and designers is very useful for online clothing shoppers. In this context, we introduce an application based on the proposed method to predict garment fit in an e-shopping environment (Fig. 7).

For a specific customer, a parametric human model is used to be adapted or adjusted to the real dimensions of the concerned human body (Fig. 8 (a) and (b)). Next, we search for the garment patterns from the database of the company according to the previous body dimensions (Fig. 8 (c)). Next, a number of red points will be marked on the selected patterns in order to measure the clothing pressures at these key positions (Fig. 8 (d)). Then, garment patterns are assembled on the adjusted digital human model (Fig. 8 (e)). Next, the assembled patterns are seamed together to form a 3D virtual garment (Fig. 8 (f)). Finally, digital clothing pressures are measured on the predefined key positions (Fig. 8 (g)).

Having performed the previous operations, the collected digital clothing pressures are introduced to the garment fit evaluation model (see the red wireframe in Fig. 7) for predicting the garment fit automatically. If the predicted result meets the customer's requirement, we recommend the concerned customer to buy the garment. Otherwise, she/he will be invited to try another one with a different size or style. This procedure repeats until the satisfaction of the result.

6.3 Limitation and future research

The limitations and future research are summarized, as follows:

1) In order to get reliable data to train the proposed method, garments with different sizes and styles need to be made firstly. As garment patterns are the business secret for fashion companies, we needed to make garment patterns and real garments by ourselves. Due to this reason, we only collected a small dataset with 72 samples to train the proposed model. Thus, further research can be combined with a specific garment company to train the proposed model using their existing clothing. As garment patterns are the business secret, our proposed approach might be only suitable for companies do both production and sale of garments by themselves.

2) The two fit levels (fit and unfit) are too simplified. For example, during the real try-on, we only evaluate the overall fit level for all the gestures and all the positions. In fact, more accurate results can be obtained if we propose to evaluate a series of local fit levels (hip fit level, waist fit level, etc.) each corresponding to one body position of the wearer and then properly aggregate them for generating an overall fit level. In this situation, all local discomfort feeling can also be considered in the fit prediction models in the further research.

3) Digital clothing pressure is selected as the index of garment fit evaluation. However, it is possible that some parts of a loose garment are not in contact with the human body and the corresponding clothing pressures could be near zero. In further research, ease allowance and clothing pressure can be combined together for evaluating garment fit in a complementary way.

4) The used digital clothing pressures are static values measured at different key positions related to a given gesture. The dynamic aspect, i.e. the clothing pressures varying with time during a movement is not considered. We need to apply time series analysis to study these clothing pressures and form new input variables of the fit evaluation model in further research.

7. Conclusion

In this research, we proposed a machine-learning-based model to predict garment fit. The results indicate that: 1) digital clothing pressure is a better garment evaluation index than ease allowance; 2) Naive Bayes is a good classifier and not inferior to other classifiers in the field of garment fit evaluation, and even better than SVMs in some cases. Compared with the traditional garment fit evaluation methods, the proposed approach has a number of advantages: 1) continuous improvement of the model's performance with new learning data, 2) independence of any real try-on, 3) removal of human involvement. Due to the dataset is very small in this research; the approach might not be easy to use in a real-life scenario. More data should be collected in the future practical applications.

Acknowledgments

This paper was financially supported by China Scholarship Council (No. 201406630077) and the Fundamental Research Funds for the Central Universities (No.CUSF-DH-D-2015082).

Reference

[1] E. Young Kim, Y.K. Kim, Predicting online purchase intentions for clothing products, Eur. J. Marketing, 38 (2004) 883-897.

[2] H.K. Song, S.P. Ashdown, Investigation of the Validity of 3-D Virtual Fitting for Pants, Cloth. & Textiles Res. J., 33 (2015) 314-330.

[3] J. Kim, S. Forsythe, Adoption of Virtual Try-on technology for online apparel shopping, J. Interact. Mark., 22 (2008) 45-59.

[4] A.S.M. Sayem, R. Kennon, N. Clarke, 3D CAD systems for the clothing industry, Intl. J. Fashion Des. Tech. Educ., 3 (2010) 45-53.

[5] X. Zhang, K. Yeung, Y. Li, Numerical simulation of 3D dynamic garment pressure, Text. Res. J., 72 (2002) 245-252.

[6] K. Liu, J. Wang, X. Zeng, X. Tao, P. Bruniaux, Fuzzy classification of young women's lower body based on anthropometric measurement, Int. J. Ind. Ergonom., 55 (2016) 60-68.

[7] E. Shin, F. Baytar, Apparel Fit and Size Concerns and Intentions to Use Virtual Try-On: Impacts of Body Satisfaction and Images of Models' Bodies, Cloth. & Textiles Res. J., 32 (2013) 20-33.

[8] J. Fan, W. Yu, L. Hunter, Clothing appearance and fit: Science and technology, Woodhead publishing Limited, Cambridge, UK, 2004.

[9] H.K. Song, S.P. Ashdown, Development of Automated Custom-Made Pants Driven by Body Shape, Cloth. & Textiles Res. J., 30 (2012) 315-329.

[10] E. Kamalha, Y. Zeng, J.I. Mwasiagi, S. Kyatuheire, The Comfort Dimension; a Review of Perception in Clothing, J. Sens. Stud., 28 (2013) 423-444.

[11] X. Tao, P. Bruniaux, Toward advanced three-dimensional modeling of garment prototype from draping technique, Int. J. Cloth. Sci. Technol., 25 (2013) 266-283.
[12] X. Chen, X. Tao, X. Zeng, L. Koehl, J. Boulenguez-Phippen, Control and optimization of human perception on virtual garment products by learning from experimental data, Knowl.-Based Syst., 87 (2015) 92-101.
[13] S. Thomassey, P. Bruniaux, A template of ease allowance for garments based on a 3D reverse methodology, Int. J. Ind. Ergonom., 43 (2013) 406-416.
[14] J. Lee, Y. Nam, M.H. Cui, K.M. Choi, Y.L. Choi, Fit Evaluation of 3D Virtual Garment, in: N. Aykin (Ed.) Usability and Internationalization. HCI and Culture, Springer Berlin Heidelberg, Berlin, Heidelberg, 2007, pp. 550-558.
[15] Z. Guo, W. Wong, S. Leung, M. Li, Applications of artificial intelligence in the apparel industry: a review, Text. Res. J., 81 (2011) 1871-1892.
[16] K. Liu, J. Wang, E. Kamalha, V. Li, X. Zeng, Construction of a body dimensions' prediction model for garment pattern making based on anthropometric data learning, J. Text. Inst., (2017). https://doi.org/10.1080/00405000.2017.1315794
[17] X. Zeng, L. Koehl, Representation of the subjective evaluation of the fabric hand using fuzzy techniques, Int. J. Intell. Syst., 18 (2003) 355-366.
[18] X. Zeng, Z. Liu, A learning automata based algorithm for optimization of continuous complex functions, Inform. Sciences, 174 (2005) 165-175.
[19] X. Zeng, D. Ruan, L. Koehl, Intelligent sensory evaluation: Concepts, implementations, and applications, Math. Comput. Simulat., 77 (2008) 443-452.
[20] A. Wong, Y. Li, P. Yeung, Predicting clothing sensory comfort with artificial intelligence hybrid models, Text. Res. J., 74 (2004) 13-19.
[21] H.-S. Kim, S.-B. Cho, Application of interactive genetic algorithm to fashion design, Eng. Appl. Artif. Intel., 13 (2000) 635-644.
[22] A. Vuruskan, T. Ince, E. Bulgun, C. Guzelis, Intelligent fashion styling using genetic search and neural classification, Int. J. Cloth. Sci. Technol., 27 (2015) 283-301.
[23] L.C. Wang, X.Y. Zeng, L. Koehl, Y. Chen, Intelligent Fashion Recommender System: Fuzzy Logic in Personalized Garment Design, IEEE Trans. Human-mach. syst., 45 (2015) 95-109.
[24] Z.-H. Hu, Y.-S. Ding, W.-B. Zhang, Q. Yan, An interactive co-evolutionary CAD system for garment pattern design, Comput.-Aided Des., 40 (2008) 1094-1104.
[25] W. Wong, S. Leung, K. Au, Real-time GA-based rescheduling approach for the pre-sewing stage of an apparel manufacturing process, Int. J. Adv. Manuf. Tech., 25 (2005) 180-188.
[26] Z.X. Guo, W.K. Wong, S.Y.S. Leung, J.T. Fan, S.F. Chan, Genetic optimization of order scheduling with multiple uncertainties, Expert Syst. Appl., 35 (2008) 1788-1801.
[27] M.-T. Lin, The single-row machine layout problem in apparel manufacturing by hierarchical order-based genetic algorithm, Int. J. Cloth. Sci. Technol., 21 (2009) 31-43.
[28] P.C.L. Hui, K.C.C. Chan, K.W. Yeung, F.S.F. Ng, Fuzzy operator allocation for balance control of assembly lines in apparel manufacturing, IEEE T. Eng. Manag., 49 (2002) 173-180.
[29] Z.X. Guo, W.K. Wong, S.Y.S. Leung, J.T. Fan, Intelligent production control decision support system for flexible assembly lines, Expert Syst. Appl., 36 (2009) 4268-4277.

[30] C. Çiflikli, E. Kahya-Özyirmidokuz, Implementing a data mining solution for enhancing carpet manufacturing productivity, Knowl.-Based Syst., 23 (2010) 783-788.
[31] Z.-L. Sun, T.-M. Choi, K.-F. Au, Y. Yu, Sales forecasting using extreme learning machine with applications in fashion retailing, Decis. Support. Syst., 46 (2008) 411-419.
[32] W. Wong, Z. Guo, A hybrid intelligent model for medium-term sales forecasting in fashion retail supply chains using extreme learning machine and harmony search algorithm, Int. J. Prod. Econ., 128 (2010) 614-624.
[33] W.K. Wong, X. Zeng, W. Au, P. Mok, S. Leung, A fashion mix-and-match expert system for fashion retailers using fuzzy screening approach, Expert Syst. Appl., 36 (2009) 1750-1764.
[34] S. Choi, Y. Yang, B. Yang, H. Cheung, Item-level RFID for enhancement of customer shopping experience in apparel retail, Comput. Ind., 71 (2015) 10-23.
[35] M. Xia, Y. Zhang, L. Weng, X. Ye, Fashion retailing forecasting based on extreme learning machine with adaptive metrics of inputs, Knowl.-Based Syst., 36 (2012) 253-259.
[36] M. Xia, W.K. Wong, A seasonal discrete grey forecasting model for fashion retailing, Knowl.-Based Syst., 57 (2014) 119-126.
[37] W.-S. Lo, T.-P. Hong, R. Jeng, A framework of E-SCM multi-agent systems in the fashion industry, Int. J. Prod. Econ., 114 (2008) 594-614.
[38] A. Pan, S. Leung, K. Moon, K. Yeung, Optimal reorder decision-making in the agent-based apparel supply chain, Expert Syst. Appl., 36 (2009) 8571-8581.
[39] K. Liu, E. Kamalha, J. Wang, T.-K. Agrawal, Optimization Design of Cycling Clothes' Patterns Based on Digital Clothing Pressures, Fiber. Polym., 17 (2016) 1522-1529.
[40] K. Liu, J. Wang, C. Zhu, Y. Hong, Development of upper cycling clothes using 3D-to-2D flattening technology and evaluation of dynamic wear comfort from the aspect of clothing pressure, Int. J. Cloth. Sci. Technol., 28 (2016) 736-749.
[41] K. Liu, J. Wang, Y. Hong, Wearing comfort analysis from aspect of numerical garment pressure using 3D virtual-reality and data mining technology, Int. J. Cloth. Sci. Technol., 29 (2017) 166-179.
[42] P. Langley, W. Iba, K. Thompson, An analysis of Bayesian classifiers, in: C.A.A.f.A. Intelligence (Ed.) Proceedings of the Tenth National Conference on Artificial Intelligence, AAAI Press, Menlo Park, CA., 1992, pp. 223-228.
[43] P. Domingos, M. Pazzani, On the Optimality of the Simple Bayesian Classifier under Zero-One Loss, Mach. Learn., 29 (1997) 103-130.
[44] C.D. enterprice, CLO 3D, in, 2016.
[45] C.N.S.M. Committee, GBT 1335.2-2008, in: Standard sizing systems for garments, Standards Press of China, Beijing, 2008.
[46] H. Seo, S.-J. Kim, F. Cordier, K. Hong, Validating a cloth simulator for measuring tight-fit clothing pressure, in: Proceedings of the 2007 ACM symposium on Solid and physical modeling, ACM, Beijing, China, 2007, pp. 431-437.
[47] L. Yanmei, Z. Weiwei, J. Fan, H. Qingyun, Study on clothing pressure distribution of calf based on finite element method, J. Text. Inst., 105 (2014) 955-961.

[48] M. Zhang, H. Dong, X. Fan, R. Dan, Finite element simulation on clothing pressure and body deformation of the top part of men's socks using curve fitting equations, Int. J. Cloth. Sci. Technol., 27 (2015) 207-220.
[49] K. DesMarteau, CAD: Let the fit revolution begin, Bobbin, 42 (2000) 42-56.
[50] H. Kim, M.L. Damhorst, The Relationship of Body-Related Self-Discrepancy to Body Dissatisfaction, Apparel Involvement, Concerns With Fit and Size of Garments, and Purchase Intentions in Online Apparel Shopping, Cloth. & Textiles Res. J., 28 (2010) 239-254.