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par

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Study on knowledge-based garment design and fit evaluation system

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Study on knowledge-based garment design and fit evaluation system

Abstract

Fashion design and fit evaluation play a very important role in the clothing industry. Garment style and fit directly determine whether a customer buys the garment or not. In order to develop a fit garment, designers and pattern makers should adjust style and pattern many times until the satisfaction of their customers. Currently, the traditional fashion design and fit evaluation have three main shortcomings: 1) very time-consuming and low efficiency, 2) requiring experienced designers, and 3) not suitable for garment e-shopping.

In my Ph.D. thesis, I propose three key technologies to improve the current design processes in the clothing industry. The first one is the Garment Flat and Pattern Associated design technology (GFPADT). Using this technology, users only input consumer's body dimensions and garment style types. As a result, garment flats and patterns can be generated automatically and simultaneously. The second one is the 3D interactive garment pattern making technology (3DIGPMT). The proposed technology provides a "what you see is what you get" way to develop garment patterns. Using this technology, users can develop customized garments rapidly for a specific body shape without any pattern making knowledge. The last one is the Machine learning-based Garment Fit Evaluation technology (MLBGFET). The Bayes classifier, neural networks and decision trees are applied to construct fit evaluation models respectively. The inputs of the proposed models are the measuring values of digital clothing pressures at different key body positions generated from 3D garment CAD software while the output is the predicted result of garment fit level: very loose, loose, normal, tight, or very tight. To construct and train the proposed models, a number of data on digital clothing pressures and garment real fit level are collected and taken as input and output learning data respectively. By learning from these input/output data, the proposed models 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, I provide a number of knowledge-based garment design and fit evaluation solutions (processes) by combining the proposed three key technologies to deal with garment design and production issues of fashions companies.

Keywords: parametric design; associated design; interactive design; construction design; pattern making; machine learning; decision trees; neural networks; Bayes classifier; garment fit prediction; digital clothing pressure

Contribution à la mise en place d'un processus automatique de création de vêtement et d'évaluation de son ajustement à partir d'une base de connaissance métier

Résumé

Le design et le bien aller d'un vêtement joue un rôle majeur pour l'industrie du textile-habillement. Les consommateurs sont en général attirés par un style ajusté et des couleurs très tendances. Ces critères sont essentiels car ils interviennent dans l'acte d'achat d'un vêtement. Afin de développer un produit ajusté à la morphologie du consommateur, designers et modélistes doivent modifier maintes et maintes fois son style et son patronage afin de satisfaire aux exigences de ce consommateur.

Actuellement, il apparait trois inconvénients majeurs dans le processus de création et d'évaluation d'un vêtement : il est très coûteux en temps pour une efficacité moindre, il est subordonné à l'expérience des designers et modélistes, il n'est pas adapté au e-commerce.

Afin de résoudre cette problématique, trois concepts à la fois technologiques et mathématiques ont été développées.

Le premier s'appuie sur l'outil GFPADT (Garment Flat and Pattern Associated design technology) permettant de créer une correspondance entre le style du vêtement choisi et la morphologie du consommateur. L'objectif final est de générer automatiquement les différents patronages du vêtement à partir d'un style choisi tout en l'ajustant aux principales caractéristiques dimensionnelles du consommateur. L'efficacité de la création en 2D des patronages en fonction de la figure de style du designer est fortement accrue.

Le second utilise l'interactivité entre deux espaces de conception 2D et 3D intégrée à l'outil 3DIGPMT (3D Interactive Garment Pattern Making Technology). Elle prend en compte le concept : "Ce que vous voyez, ce que vous obtenez". Une première étape consiste à ajuster le vêtement directement en 3D sur un avatar représentatif du consommateur à partir des caractéristiques principales du dessin de style avec une stratégie bien définie. La seconde étape utilise conjointement l'avatar et le vêtement en 3D afin de compléter le design de celui-ci avant sa mise à plat définitive.

Cette stratégie de conception permet de développer rapidement un modèle de vêtement ajusté pour des clients de différentes mensurations sans aucune connaissance du métier.

Le dernier appelé MLBGFET (Machine learning-based Garment Fit Evaluation Technology) évalue l'ajustement du vêtement par un apprentissage automatique. Le classificateur de Bayes, le réseau de neurones et l'arbre de décision ont été respectivement appliqués afin de créer un modèle d'évaluation de l'ajustement. Les entrées du modèle sont les valeurs mesurées des composantes principales influençant l'ajustement du vêtement, telles que la pression numérique du vêtement pour différents zones. Les sorties sont les résultats de prédiction des conditions d'ajustement du vêtement, tels que sa validation par oui ou non. A partir de cet apprentissage de données collectées, ce modèle peut prévoir rapidement et précisément si le vêtement s'ajuste sans le moindre essayage. Par conséquent, cet outil peut être appliqué à l'élaboration de vêtements, mais peut aussi être appliquée à la vente en ligne lors de l'évaluation de l'ajustement.

Finalement, nous avons fourni des solutions de conception et d'évaluation de vêtements basées sur la connaissance en intégrant ces trois concepts basés sur des technologies clés pour résoudre certains problèmes de conception et de production de vêtements dans les entreprises de mode.

Mots clés: conception paramétrique et associative, design interactif, dessin de style, modélisme, apprentissage automatique, arbre décisionnel, réseau de neurones, classifieur de Bayes, évaluation de l'ajustement du vêtement, pression vestimentaire.

基于知识的服装设计与评估系统的研究及应用

摘要

服装设计与评估在服装行业起着至关重要的作用。一件服装的款式和合体性这二个主要因素直接关系到客户是否购买该服装。为了开发一件合体的服装，设计师和制板师需要多次调整服装的款式和纸样至到他们的客户满意为止。目前，这种传统的服装设计与合体性评估有三个主要的缺点：1）非常耗时且效率低下 2）需要经验丰富的设计师和制板师 3）服装的合体性需要制作出真实的服装并由真人试穿才能准确地评估。

在该课题研究中，笔者提出三项关键的技术试图解决传统服装设计与评估所面临的一些棘手的问题。第一项是服装款式和结构关联设计技术，在该技术的辅助下，使用者只需要输入人体的主要尺寸参数和服装的款式参数，服装的款式图和此款式图所对应的结构图会自动生成出来。该技术把传统属于分离状态的服装款式设计和结构设计整合到一起，明显地提高了服装款式设计和结构设计的效率；第二项技术是 3D 交互式服装纸样开发技术。该技术以一种“所见即所得”的方式开发服装的纸样。在该技术的辅助下，使用者无需服装纸样开发的经验和知识就可以快速的为不同体型的客户开发出合体性较好的服装纸样；第三项是基于机器学习的服装合体性评估技术。贝叶斯分类器、决策树以及神经网络等机器学习算法分别应用于构建服装合体预测模型。该模型的输入项是影响服装合体性的关键因素，如服装压力测量值；同时该模型的输出项为服装合体性预测的结果，如松的、紧的、正常的等。通过从现有的服装压力测量数据以及合体性评估数据中不断的学习，该合体性预测模型可以在不需要真实试穿的情况下快速准确地预测服装的合体性。该技术可以很好地应用到服装产品的开发以及服装网络销售。

最后通过整合服装款式和结构关联设计技术、3D 交互式的服装纸样开发技术以及基于机器学习的服装合体性评估技术，本课题的研究为当前服装企业的设计、生产以及销售所面临的一些棘手问题提供了基于知识的服装设计与评估系统的可行性解决方案。

关键词：参数化设计；关联设计；交互设计；款式设计；结构设计；3D 服装设计；制板；机器学习；决策树；神经网络；贝叶斯分类器；服装合体性评估；数字化服装压力。

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The completion of this thesis is the terminal point of my Ph.D. study; however, it is also a new starting point for my life. I will still hold fast to my dream in the future.

"The body was not moved; however, the heart is already far. How far the dream is, how long the road is."

Kaixuan LIU

January 20th, 2017

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LIST OF ABBREVIATION

2D——two Dimensional

3D——three Dimensional

3DIGPMT——3D Interactive Garment Pattern Making Technology

A——Abdomen circumference

AH——Abdomen height

BP-ANN ——Back Propagation Artificial Neural Networks

CD——Crotch Depth

CW——Crotch Width

DWH——the Drop of Waist-to-Hip

GFPADT——Garment Flat and Pattern Associated design Technology

HH——Hip Height

H——Hip circumference

IL——Inside Length

ID3——Iterative Dichotomiser 3

KH——Knee height

K——Knee circumference

MLBGFET——Machine learning-based Garment Fit Evaluation Technology

h——Stature

T——Thigh circumference

WH——waist height

W——Waist circumference

GENERAL INTRODUCTION

With the rapid economic development, the consumers' demand for personalization is becoming stronger than before. The production models in clothing industry change from cottage industry type to mass production, then to mass customization in order to be adapted to the market changes and costumers' requirements. Mass customization requires clothing enterprises producing customized garments rapidly according to different body shapes and individual requirements. However, the sophistication in consumers' demands and fast fashion result in increased difficulties in clothing design. There are two ways to solve this issue in the clothing industry: 1) employing more designers; 2) changing current design methods or processes. Hiring more designers having rich experiences will increase the costs significantly. Obviously, changing current design methods or processes is an efficient way to overcome the difficulties in the modern clothing companies.

The design department is one of the key departments in all fashion companies. Traditional fashion design and pattern making are strongly related to practical and empirical work. It takes several years and even more than ten years for a novice to master fashion design or pattern making skills. Therefore, the designers and pattern makers having rich experiences are scarce resources for a fashion company, and their demission will be a fatal strike for their company. To develop block patterns, fashion designers, pattern makers and technologists need repeated consultations and communications. After this stage, several testing specimens are carried out to evaluate whether the designed garment is fit or not. This process not only needs designers and pattern makers having concerned work experience for years but also is very time-consuming. Actually, the garment style and fit mainly depend on the skill level of designers and pattern makers. Therefore, how to develop garment products without experienced designers and pattern makers can be very useful for fashion companies. Thus, fashion companies can reduce their dependence on designers and pattern makers.

In the background of globalization, the garment industry is still a typical low-tech, labor-intensive industry. Although the technologies of artificial intelligence such as machine learning, expert system have been widely used in a vast range of industrial fields for improving the quality of products, processes and management, they are rarely exploited in the field of fashion design and fit evaluation. This is mainly due to the uncertainties and imprecisions existing in the design knowledge, which is usually tacit and difficult to be extracted and expressed. Actually, a number of researches have shown that the tacit design knowledge could also be extracted and expressed with mathematical modeling and simulation techniques. After modeling the designers' knowledge, the novices can develop garment products rapidly and efficiently with the help of knowledge-based models in order to meet the complex market changes and the customers' individual needs.

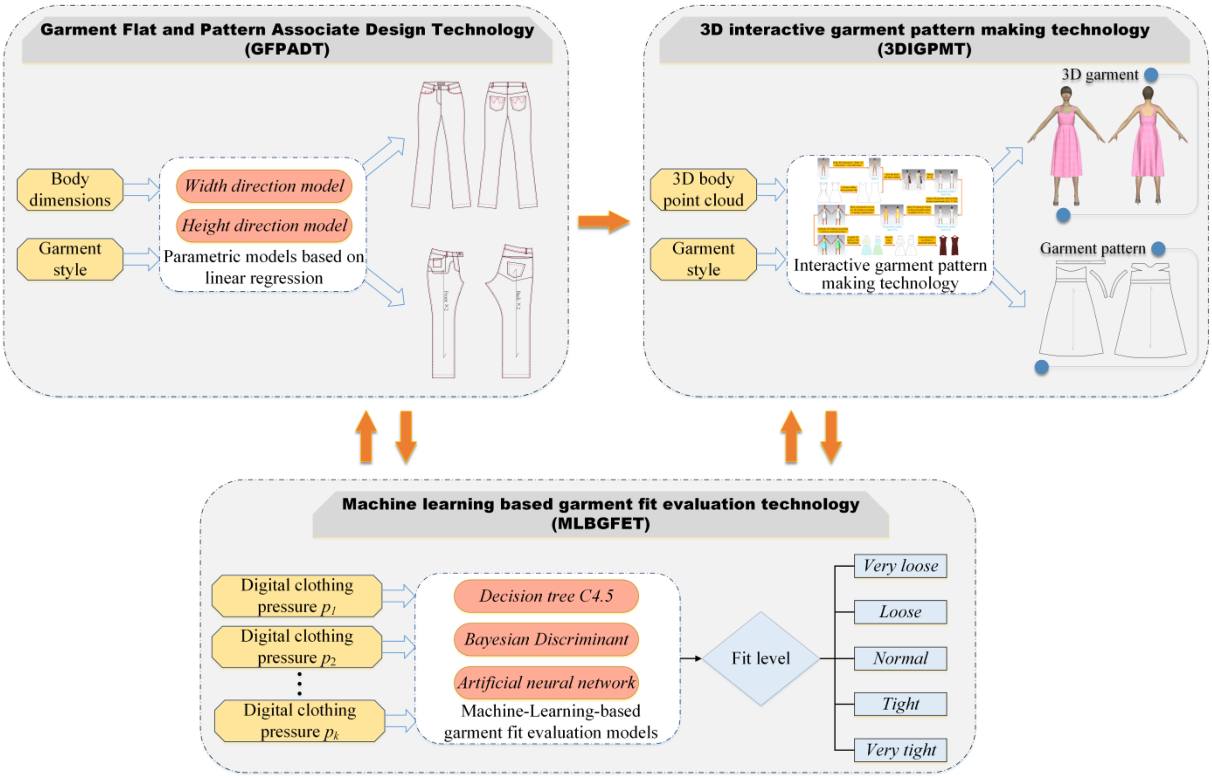


Figure 0-1 Knowledge-based garment design and fit evaluation system.

In my Ph.D. research, I propose a knowledge-based garment design and fit evaluation system by integrating experts' knowledge, experimental data and customers' individual needs for supporting designer's work. As shown in Figure 0-1, this system includes three new technologies: the Garment Flat and Pattern Associated design Technology (GFPADT), the three Dimensional Interactive Garment Pattern Making Technology (3DIGPMT) and the Machine learning-based Garment Fit Evaluation Technology (MLBGFET). GFPADT permits to use several key parameters, such as garment style and body dimensions, to generate garment flats and patterns rapidly. 3DIGPMT enables to use the way of "what you see is what you get" to develop garment patterns. Using this technology, users can develop customized garment products rapidly without any pattern making knowledge. MLBGFET permits to apply a number of artificial intelligent tools, such as neural networks and decision trees, to construct fit evaluation models. After learning from the experimental data on real and virtual try-on, the proposed models can predict garment fit level automatically without any real try-on. Finally, the three proposed technologies (GFPADT, 3DIGPMT and MLBGFET) are integrated into a knowledge-based garment design and fit evaluation system to help designers to develop and evaluate garment products. Compared with traditional fashion design and evaluation methods, the proposed knowledge-based garment design and fit evaluation system has the advantages of rapidity and simplicity. Also, users do not require specialized fashion design knowledge when making operations on this system.

The aim of my Ph.D. research is to address a series of key issues encountered in the fashion design and provide several more efficient and more reasonable solutions for fashion companies. In practical applications, the proposed technologies have already brought economic benefits in a clothing enterprise in China.

The overall layout of the thesis is organized as follows:

CHAPTER 1: ***State of the art***

I expound the basic concepts of fashion illustration drawing, garment flat drawing, garment pattern making, 3D garment design, garment fit evaluation, etc. Then I present recent research progress in these fields in detail and analyze the disadvantages of the current fashion design and fit evaluation methods and processes. Finally, I raise the research purposes, significances and methods on the development of a knowledge-based garment design and fit evaluation system.

CHAPTER 2: ***Computational tools for modeling***

For formalizing and modeling fashion designers' knowledge, I propose a systematic approach combining the use of linear regression, Bayes classifiers, decision trees and artificial neural networks. Therefore, in this chapter, I first introduce the theoretical basis of the computational tools that are concerned in our approach. Then, the merits and faults of these computational tools are expounded. Finally, I construct different knowledge models according to the characteristics of different computational tools. For example, linear regressions are applied to model the relations between key design parameters, garment flats and patterns, while Bayes classifiers, decision trees and artificial neural networks are used to model the relation between digital clothing pressures and garment fit level.

CHAPTER 3: ***Garment flat and pattern associated design technology***

Flat drawing and pattern making are two main parts of fashion design. Currently, flat drawing and pattern making belong to different departments in fashion companies. This phenomenon results in high cost and low efficiency in the garment products development. In this chapter, I proposed GFPADT to combine garment flat drawing and pattern making together. By extracting and analyzing experts' knowledge and data, garment flats and patterns are represented by several common parameters. After this stage, linear regression is applied to model the relation between garment flats, garment patterns and the parameters. Based on the theory of GFPADT, I have developed a software application named "Associated design system for jean Flat and Pattern 2016" (ADSFP 2016) to generate jeans' flats and patterns. With the help of ADSFP 2016, garment flats and the corresponding patterns can be generated simultaneously and automatically.

CHAPTER 4: ***3D Interactive garment pattern making technology***

Garment pattern making is a highly technical work in fashion companies. In this chapter, I proposed 3DIGPMT to develop garment pattern with the way of "what you see is what you get". For realizing the proposed method, the two Dimensional (2D)-to-three Dimensional (3D) virtual try-on technology is used to model 3D garment surfaces. After this stage, 3D-to-3D fashion design technology is used to adjust 3D garment to meet design requirements. Finally, the 3D-to-2D flattening technology is applied to unfold 3D garment's surface into 2D garment patterns. Through human-computer interactions, the complexity of garment patterns making can be largely reduced. With the help of 3DIGPMT, users can develop customized garments for different body shapes without any professional skills.

CHAPTER 5: ***Machine learning-based garment fit evaluation technology***

The fit of a garment has always been a key factor in determining whether a customer buys it. Therefore, how to evaluate garment fit is not only very important for designers, but also for consumers and retailers. In this chapter, I propose a machine learning-based method to evaluate garment fit. First, a Naive Bayes classifier, a decision tree C4.5 and a Back-propagation Artificial Neural Network (BP-ANN) are used for constructing fit evaluation models respectively. Then, the constructed models learn from the data of digital clothing pressures and garment fit level collected by virtual and real try-on. Finally, the trained models predict garment fit by inputting the corresponding digital clothing pressures. Compared with traditional garment fit evaluation methods, MLBGFET can predict garment fit rapidly and automatically without any real try-on. This technology can be well applied to made-to-measure, mass customization, garment e-shopping, etc.

CHAPTER 6: ***Applications of knowledge-based garment design and fit evaluation system***

Based on GFPADT, 3DIGPMT and MLBGFET developed in Chapter 3, Chapter 4 and Chapter 5, I proposed four applications (processes) for developing and evaluating garment products in the areas of mass production, made-to-measure, mass customization and online shopping. The first process aims at developing garment flats and patterns automatically and simultaneously for mass production. The second one enables to make personalized garment patterns and evaluate their fit for made-to-measure. The third one permits to develop garment patterns rapidly for mass customization by combining the previous three technologies. The last one permits to evaluate garment fit rapidly and automatically without real try-on for garment e-shopping. As the garment experts' professional knowledge has been modeled and successfully integrated into the proposed system, the users do not need to master any knowledge and experience in fashion design, pattern making and fit evaluation.

CHAPTER 1: STATE OF THE ART

In this chapter, I state traditional methods of garment design and fit evaluation. By analyzing the current methods of fashion illustration drawing, garment flat drawing, pattern making, 3D garment design and fit evaluation, I clearly indicate the main drawbacks existing in the current design processes and provide a number of orientations to improve these processes.

1.1 Traditional garment design processes

Fashion design mainly includes three key parts: style design, construction design and process design. The main work of style design is fashion illustration drawing and garment flat drawing [1], the main work of construction design is pattern making [2], and the main work of process design is process sheet making. Fashion designers draw garment flats according to fashion illustration; pattern makers make garment patterns according to garment flats [3]; and technologists make production process sheets based on the garment flats and patterns. The three basic designs complement each other.

1.1.1 Fashion illustration drawing

Figure 1-1 Fashion illustrations.

Fashion illustration, also called effect drawing, fashion drawing, is the transmission of fashion through a diagram. Fashion illustration has been used for nearly 500 years. Ever since clothes have been in existence, and there has been a need to translate an idea or image into a fashion illustration. Not only do fashion illustrations show a representation or design of a garment but they also serve as a form of art. Fashion illustration shows the presence of hand and is said to be a visual luxury [4-5].

In fashion companies, fashion illustration is a visual aid through which a design can be explained and communicated between concerned professional experts (designers and pattern makers). Fashion illustration drawing requires designers using the numerous materials like pencil, pen, ink, charcoal, watercolor, polaroid film, etc. All these materials are used to make the illustration sharper and next to real to make sure that convey the style in its best sense. Since fashion illustration is used to convey designs, the designers who prepare fashion illustrations should keep in mind that they should use colors and details that highlight the edges of the clothes to make it more attractive. There has to be a good balance between the colors and the sketching to achieve the masterpiece [6]. Fashion illustration drawing requires professional knowledge on fashion design such as aesthetics, ergonomics and painting. Because of this, fashion illustration is something that requires expert hands without which the illustration could not be presented in its best form. For an illustration to speak in words, it is very important to draw in such a way in which each angle of the illustration should express designers' design concept. In order to emphasize some garment parts, designers usually use a number of exaggerations to draw fashion illustration on these parts. As shown in Figure 1-1, these fashion illustrations show designers' concept using exaggeration. Instead, a garment flat should reflect real garment details as much as possible. This is one of the main differences between fashion illustration and garment flat drawing.

1.1.2 Garment flat drawing

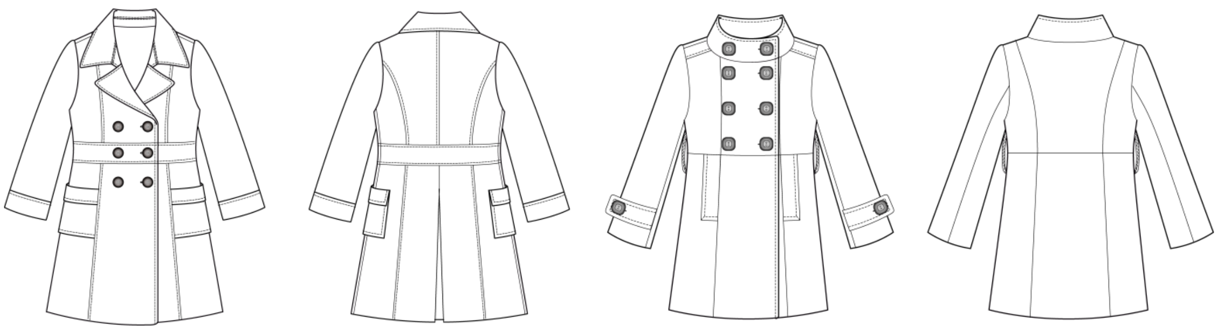


Figure 1-2 Garment flats.

Garment flat also called flat sketches, flat drawing, technical flat, or just "flat" in the fashion industry, is a black and white fashion technical drawing that shows a garment as if it was laid flat to display all seams, topstitching, hardware, and any other design details (Figure 1-2). Flats are used to concretely express designers' ideas and garment details to related-departments [7]. Generally, garment flats are applied to many places, for example, patternmaking documentation, technology packs, specifications, cost sheets, 3D virtual garment modeling [8, 7, 9-14]. In order to avoid misunderstanding in sampling and production, garment flats are drawn in detail [10, 13]. Actually, garment flats focus on the tangible apparel or the actual garment which is to be produced [12]. It is always about the actual garment, rather than a general idea of a garment.

Like fashion illustration drawing, flat drawing also needs professional knowledge on fashion design. It is difficult for people without related skills to draw garment flats. Currently, there are two methods to draw garment flats. One is drawing by hand, which is called “manually drafted”; the other is the use of special design software, like Adobe Illustrator, CorelDraw, Kaledo style, that is called “computer-aided drafting”. Both of flat drawing methods require a superior drawing skills [15]. For avoiding distraction, flat drawing does not require much movement or shading. A neatly detailed garment flat simply means how well in detail you can illustrate your design requirements to related production departments [8]. Generally, the garment flat is drawn on white paper using black lines [8, 14], because black lines are easier for people to follow visual guidelines and provide a clearer representation of designers’ ideas. However, usually, there are still some misunderstandings of styles’ details between designers and pattern makers, no matter how accurate the garment flats are.

1.1.3 Garment pattern making and pattern grading

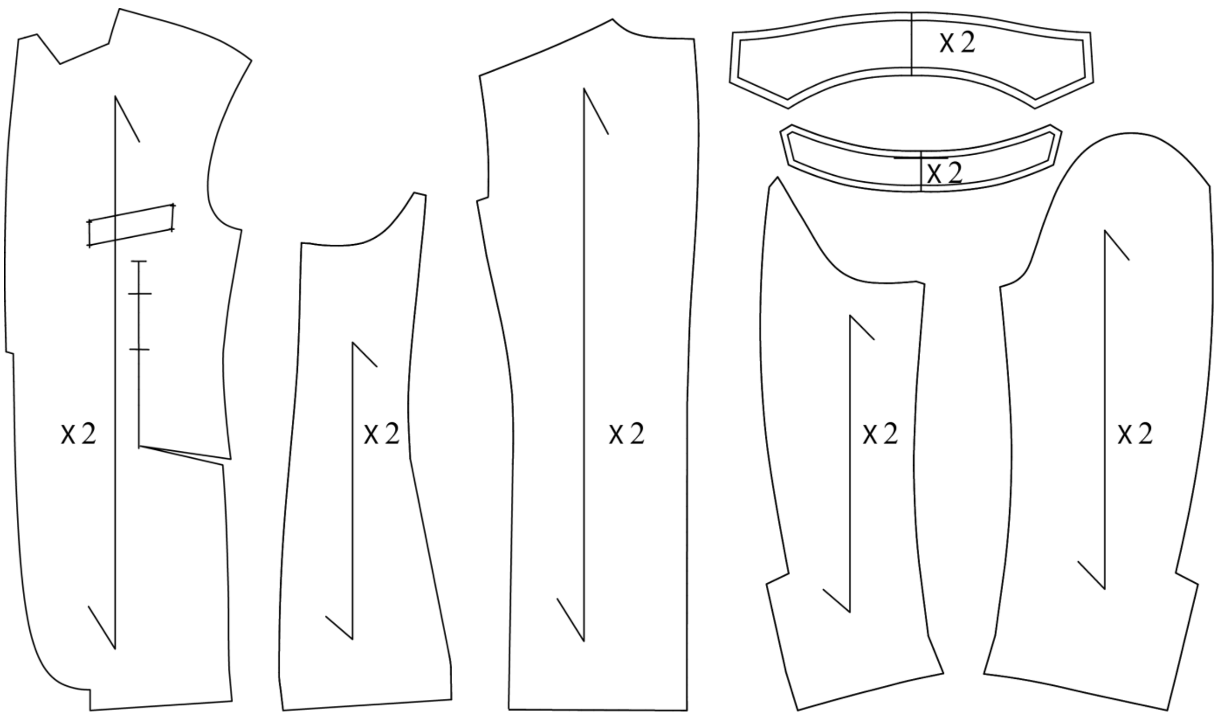


Figure 1-3 Garment patterns.

In sewing and fashion design, garment patterns are templates from which the parts of a garment are traced onto fabric before being cut out and assembled (Figure 1-3). Patterns are usually made of paper and are sometimes made of sturdier materials like paperboard or cardboard if they need to be more robust to withstand repeated use. The process of making or cutting patterns is sometimes condensed to the one-word patternmaking but it can also be written pattern making, pattern cutting, construction design, pattern cutting, etc. Traditional pattern making process refers that pattern makers draw garment construction lines on a brown paper according to the garment flat provided by designers. After this, they cut the paper along the construction lines to acquire many paper pieces used for cloth cutting. The work of pattern making likes a bridge between fashion design and clothing making [16]. Pattern making, relying heavily on pattern makers' experience obtained by many years related work, is considered as one of the highest technical works in the clothing companies. Currently, there are mainly two methods to make garment pattern: the traditional hands-on approach and the computer-aided process, both requiring sophisticated skills. A novice needs to take several years to be proficient in this technique. It results in that the current methods of pattern making are not easy to spread [17].

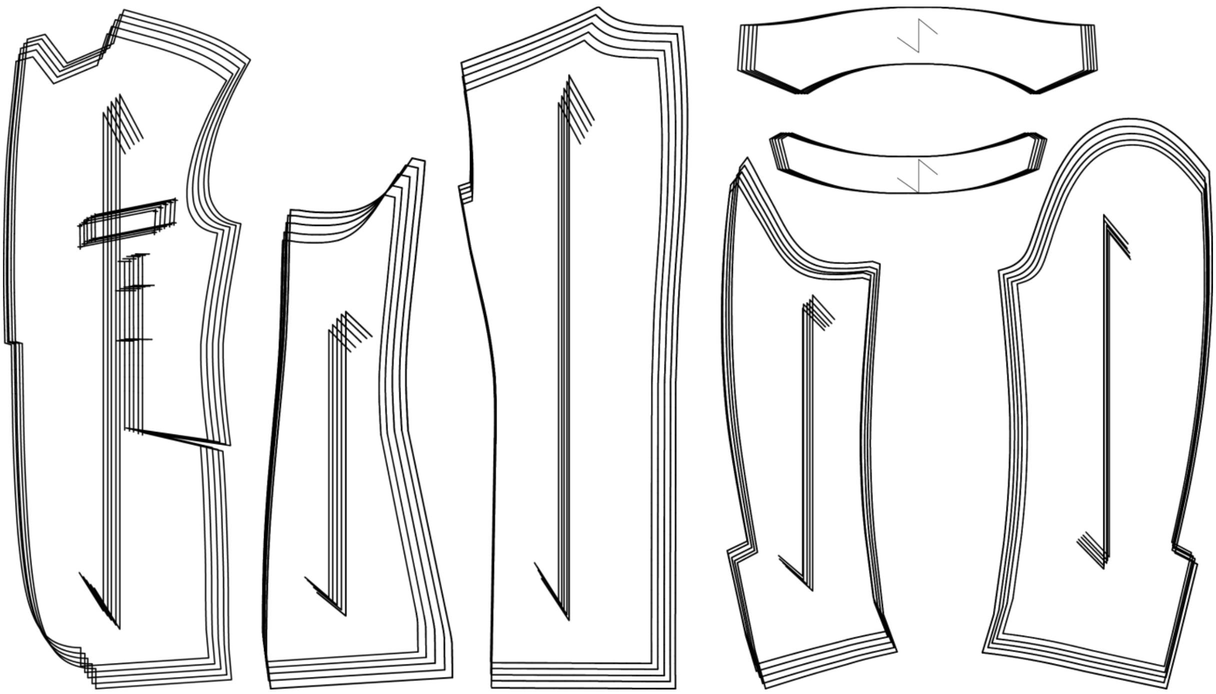


Figure 1-4 Pattern grading from one initial pattern (standard size) to a number of sizes.

Pattern grading is the extension of pattern making. As pattern making is very time-consuming, in order to save time and keep the ready-made patterns' shapes, the ready-made patterns are enlarged or shrunk to fit different body size and shapes (Figure 1-4). This process is called pattern grading. Pattern grading enables to proportionally increase and decrease pattern sizes according to specific instructions. It is an essential part of pattern making for the ready-to-wear garment production. Generally, pattern grading adjusts for people of different ages and genders. The fabric type also influences the pattern grading rules [18]. The cost of pattern grading is incomplete without considering marker making [19].

1.1.4 Production sheet making

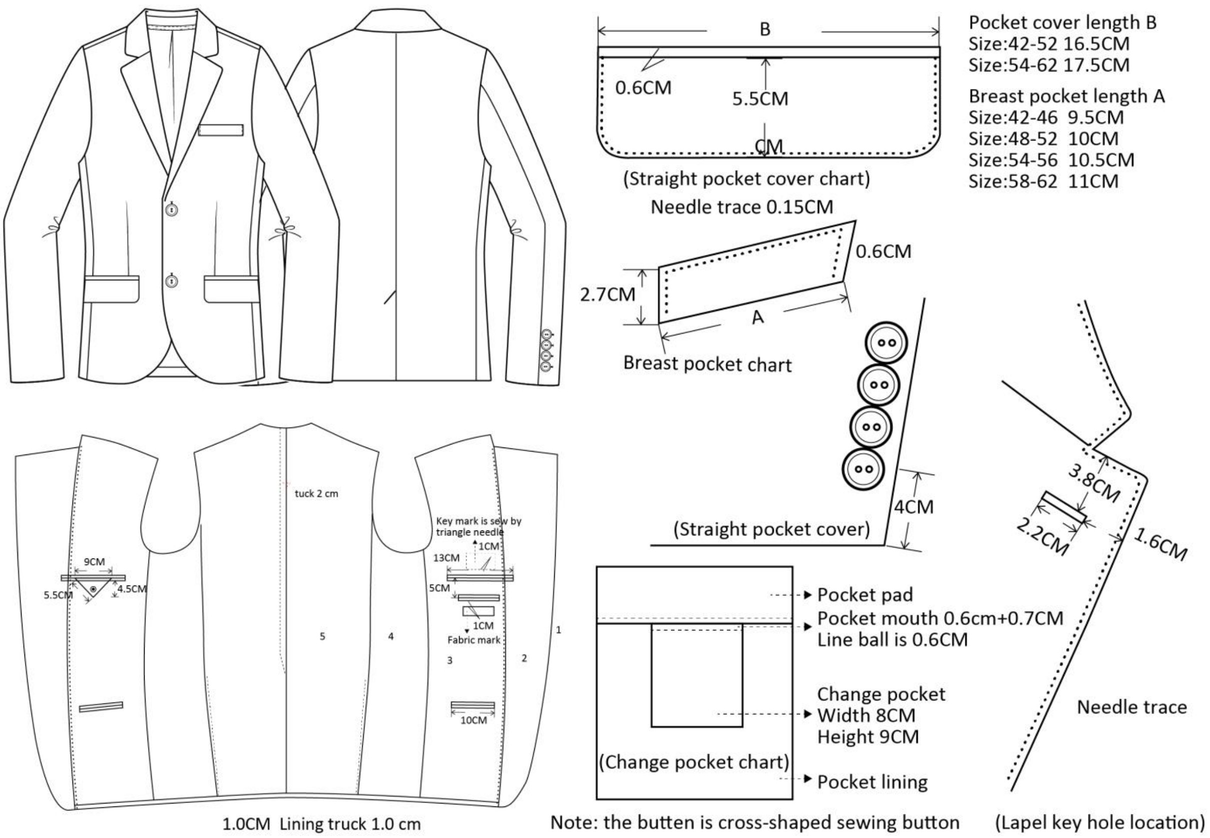


Figure 1-5 Garment production sheet.

During garment making process, workers need a file to guide how to sew. That is the point of production sheet making. Production sheet provides detailed instructions about every aspect of a garment’s design and construction, like fabrics, trim, artwork or graphics, label information, packaging instruction, and even tiny-but-mega-important details like desired stitching should all be included in the production sheet to reduce the chances of misunderstandings (or shortcuts by the factory) (Figure 1-5). The production sheet tells the producer (factory) all the information that is needed to successfully transform your design into a product that is exactly how designers envisioned it. An excellent production sheet will reduce errors in production, reduce issues with communication, and ultimately can save fashion companies tons of money and frustration [20].

1.1.5 Discussion

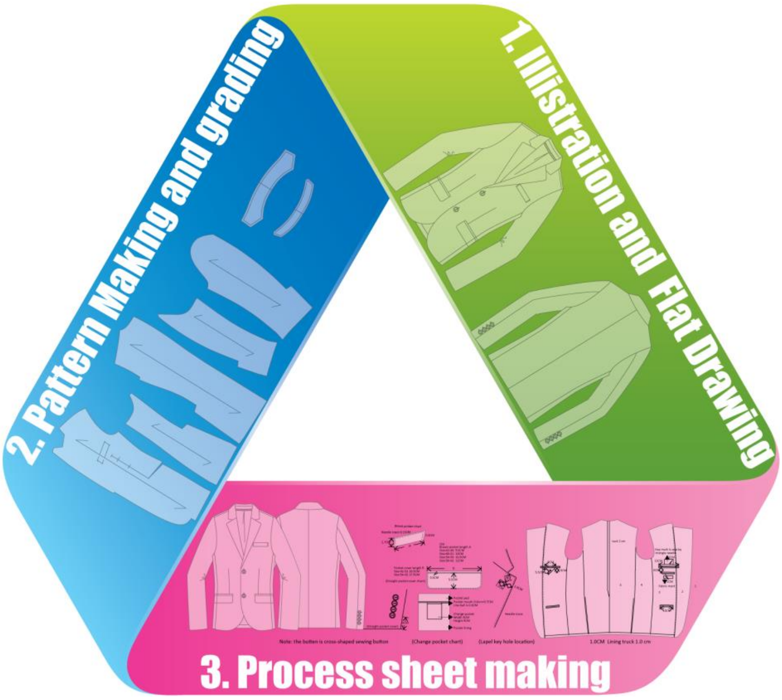


Figure 1-6 Relations between illustration and flat drawing, pattern making and grading, and production sheet making.

Fashion designers draw fashion illustrations and garment flats to express their design concepts concretely, and pattern makers make patterns according to customers' body dimensions and garment flats drawn by designers [21]. As garment flat drawing and pattern making affiliate with different departments in fashion companies, fashion designers and pattern makers should communicate repeatedly to modify garment flats and their corresponding patterns until they are satisfied. This process is time-consuming and inefficiency. Thus, some scholars proposed several new technologies to develop garment flat or pattern rapidly, such as, 3D-to-2D flattening technology [22-36], 2D-to-3D virtual try-on and modeling technology [37, 32-33], 3D-to-3D garment editing [38], parametric pattern making technology [39-40], rapid garment flat generation technology [7, 3]. However, none of the previous research studies involved how to combine the work of flat drawing and pattern making together.

As shown in Figure 1-6, illustration and flat drawing, pattern making and grading, and production sheet making are all interrelated. This makes up the whole garment design and production. Generally, fashion illustration drawing and garment flat drawing belong to artistic design; however, pattern making and production sheet making are affiliated with engineering design. This leads to different approaches between garment flat drawing and pattern making.

Most of style designers cannot make garment patterns; likewise, most of pattern makers are unable to draw garment flats. The gulf between garment flat drawing and pattern making results in that the two design processes belong to two completely separate departments in most of fashion companies. In this case, garment enterprises need to hire more manpower and to spend more money into these two departments. Moreover, the communication between these two departments can also lead to lower efficiency of the garment products development. If flat drawing and pattern making can be integrated together, the fashion design efficiency will be improved significantly. Therefore, I integrate garment flat drawing and pattern making together in this Ph.D. thesis. The corresponding work, i.e. Garment Flat and Pattern Associated design Technology (GFPADT) has been presented in Chapter 3.

1.2 3D garment design

1.2.1 3D-to-2D

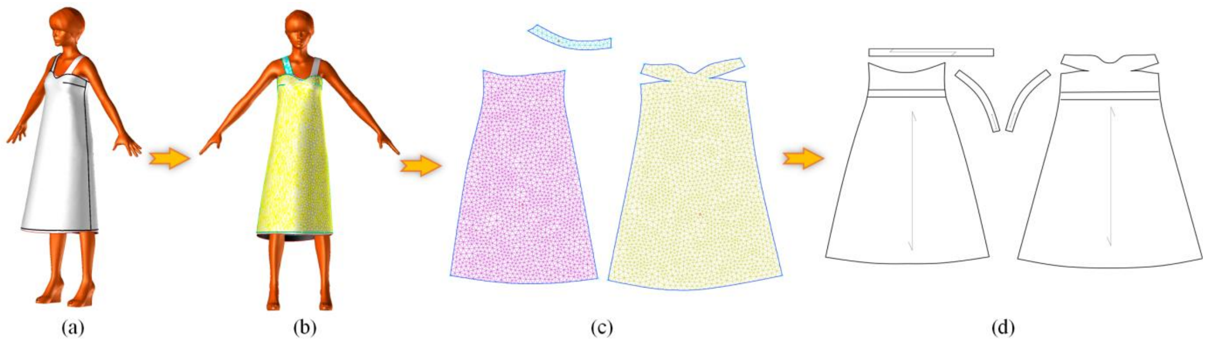


Figure 1-7 3D-to-2D flattening.

In order to solve garment-fitting issues and reduce the complexity of the problem to an acceptable level, various three-dimensional (3D) to two-dimensional (2D) flattening methods have been proposed and developed to obtain garment patterns. Figure 1-7 shows a classical 3D pattern making approach. Firstly, a number of construction lines are drawn on the 3D garment's surface (Figure 1-7(a)). Then a number of 3D surfaces are generated according to these lines (Figure 1-7(b)). Next, these 3D surfaces are flattened into 2D patterns after a meshing process of these different surfaces (Figure 1-7(c)). Finally, the unfolded patterns are modified slightly to meet the requirements of industrial production (Figure 1-7(d)).

Due to a good application prospect of 3D-to-2D flattening technology, many scholars used this technology to develop garment pattern. Hinds et al. proposed a 3D mathematical model based on the gaussian curvature to unfold 3D surfaces into 2D patterns for garment pattern development in their research [22]. While Kang and Kim constructed a fitting 3D garment for a special mannequin then unfolded the 3D garment to acquire its 2D patterns [17]. Jeong et al. used triangular meshes to construct a 3D garment surface and pieced these triangular meshes together in a 2D plane to obtain tight-fitting clothing pattern [24, 28]. Au et al divided the surface of a 3D virtual dummy into many areas according to the human body's characteristic line and transformed the 3D surface of the prototype garment to a 2D cutting pattern [41, 27]. Daanen and Hong used a 3D body scanner to collect the point cloud of waist-to-hip part; then the points in the 3D scan were converted to triangles and these triangles were thereafter merged with neighboring triangles of similar orientation until about 40 triangles remained; these triangles were sewn together to form a "patchwork"-skirt finally [42]. Choi and Nam studied the pattern unfolding issues of different upper lateral body types [25]. Jin et al. modeled a 3D garment with constrained contour curves and style curves. They then flattened the 3D garment's surface based on these curves [26]. Bruniaux et al. constructed 3D garment construction curves around a 3D mannequin and generated 3D surfaces based on these curves. Next, they obtained garment patterns by flattening the obtained 3D surfaces [30-33, 43]. Zhang et al. proposed a method to model the 3D upper garment with ease allowance for pattern making [34]. Yan et al. drew 3D garment construction curves on a 3D model of a disable female; then using these construction curves to simulate a 3D garment; the garment patterns were obtained by flattening the 3D garment finally [36]. However, there are four shortcomings existing in the aforementioned research studies: 1) the proposed methods are too complex to be realistically implemented in production processes; 2) they are limited to simple styles and can hardly be applied to complicated styles; 3) they are restricted to tight garments and involve little ease allowance; 4) they did not consider all factors affecting the appearance of a garment such as fabric mechanical properties in a virtual environment.

1.2.2 2D-to-3D

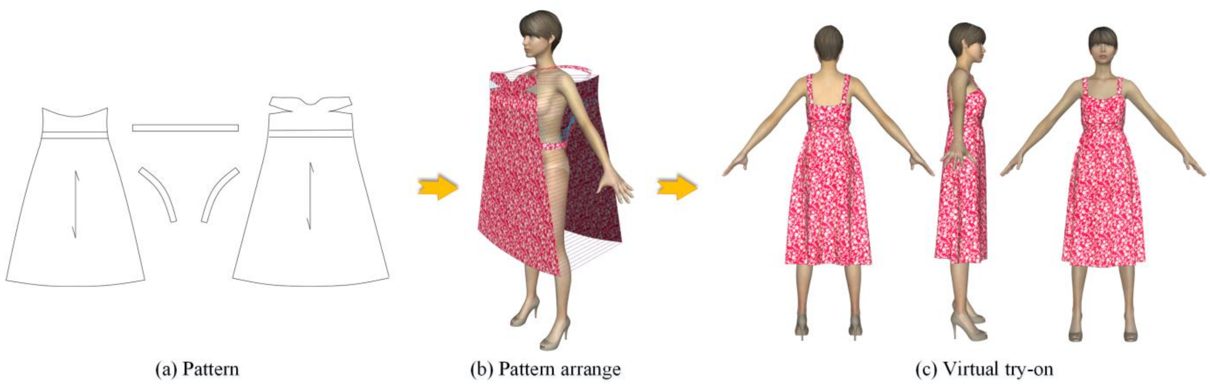


Figure 1-8 2D-to-3D virtual try-on.

Virtual try-on technology was developed to evaluate garment fit [44-45], model 3D garment for animation, etc. This technology has been widely applied in the clothing and animation industry in the last ten years. Figure 1-8 shows a classical virtual try-on process. Fist, pattern maker makes a set of patterns using traditional methods (Figure 1-8a). Then these patterns are input into a virtual try-on software programme. Next, the patterns are arranged around an avatar (Figure 1-8b). These patterns are sewn together finally (Figure 1-8c).

Currently, a number of commercial virtual try-on software, such as $Clo\ 3D$, $Lectra\ 3D\ Prototype$, $OptiTex$, $V-Stitcher\ 3D$, are available on the market for fashion design and evaluation [46]. These 3D virtual try-on software systems follow the similar principles, i.e. showing virtual garment static and dynamical performance from identified human morphological and fabric properties and their interactions using complex mechanical and geometric modeling and simulation techniques [47]. They normally include four main modules: 1) a 3D parametric mannequin module, 2) a fabric properties module, 3) a virtual pattern-sewing module, and 4) a draping module [48-49, 46]. In order to model human body rapidly, the function of the 3D parametric mannequin module is to construct a personalized 3D human model from measures of a 3D body scanner or a measuring tape, related to a specific customer [50-51]. Several key body dimensions, such as height, waist circumference, hip circumference, control the parametric mannequin's dimensions. By adjusting the key body dimensions, the 3D parametric mannequin module can create various body shapes and dimensions rapidly and automatically, in order to meet customers' body shapes and dimensions. Then, the fabric properties module, usually based on a mechanical model, will permit to simulate different perceived properties (draping, texture, elasticity, bending, etc.) of a virtual fabric by adjustable fabric technical parameters according to the nature of the corresponding real fabric. After this, the virtual pattern-sewing module assembles the predefined garment patterns on the specific 3D human body and sews the patterns together by taking into account the performances of the simulated fabric. Finally, the draping module simulates gravity, wind, draping, etc. The combination of these four modules constitutes a virtual try-on system, permitting to simulate the process of real garment making. In a virtual 3D try-on process, consumers and designers can visualize the static and dynamic performances 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 [52].

1.2.3 3D-to-3D

Figure 1-9 3D-to-3D fashion design.

In order to model a 3D garment rapidly, a new method of 3D-to-3D fashion design enables to modify the prototype directly in order to obtain the expected styles. As shown in Figure 1-9, a long dress is transformed into other dresses through adjusting the length, collar, sleeve and so on. Currently, there are mainly two methods to realize 3D-to-3D fashion design: the first method: through a series of modifications of the 2D garment patterns, the 3D garment changes correspondingly [53-54]; the second method: through modifications of the surfaces on the 3D garment, I can obtain the expected style directly [55]. Like a procedure of sculpture, the second method requires operators to master experienced skills and the process of surface modification is complex and time-consuming. Instead, the first method is highly efficient and easy to operate. However, this method requires accurate 2D garment patterns and other technical parameters firstly.

1.2.4 Discussion

With the development of 3D technology, the 3D fashion design will have the trend to replace the traditional fashion design methods in the future [56]. However, due to some technical restriction, the traditional fashion design and 3D fashion design will coexist for a very long time. Currently, designers should use both approaches in a complementary way to develop new garment products [56]. The 2D-to-3D virtual try-on technology can help designers to check whether the garment style is feasible [44]; the 3D-to-2D flattening technology can help pattern maker to develop garment patterns [57-58, 36]; and the 3D-to-3D fashion design can help designers to design 3D garments [55]. However, neither the 2D-to-3D virtual try-on technology nor 3D-to-3D garment transformation approach nor 3D-to-2D flattening technology can work alone effectively. Therefore, I wish to integrate the above three technologies together in my Ph.D. thesis. In this context, 3D Interactive Pattern Making Technology (3DIPMT) is proposed in Chapter 4.

1.3 Garment fit evaluation

1.3.1 Garment fit

The issue of garment fit always runs through the entire garment design, production and sale processes. In fashion design process, designers and pattern makers need to evaluate garment fit for garment products optimization. In garment retail field, the major issue that concerns the customers is garment fit [59-62]. No matter how beautiful garments are, how excellent fabrics are, customers still do not purchase the garments if they are unfit [63]. Currently, more and more people buy garments online [64]; however, the bottleneck, how to evaluate garment fit, hampers the development of clothing e-business [65]. Researches showed that more than 50% customers are dissatisfaction with garment fit [66-68]. High perdition 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 online cannot be tried on [69-70]; 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 the main problems that must be solved for the clothing industry.

There are many factors influencing garment fit; nevertheless, what is fit? Up to now, this concept has not been defined exactly. Cain pointed out 'Fit is directly related to the anatomy of the human body and most of the fitting problems are created by the bulges of the human body' [71]. H and E considered that 'clothing that fits well, conforms to the human body and has adequate ease of movement, has no wrinkles and has been cut and manipulated in such a way that it appears to be part of the wearer.' [72]. Shen and Huck believed that 'clothing which fits, provides a neat and smooth appearance and will allow maximum comfort and mobility for the wearer.' [73]. By summarizing the above fit definitions, I believe that clothing fit mainly includes two aspects: aesthetic fit and comfort fit. The comfort fit is mainly related to fabric materials and manufacturing processes, while the aesthetic fit is mainly determined by fashion styles. Meanwhile, the other design factors such as garment patterns and body dimensions influence both aesthetic fit and comfort fit. Due to the limitation of time and energy, I only study the evaluation of the garment comfort fit caused by garment size, patterns and materials. The aesthetic fit is not considered here.

1.3.2 Garment fit evaluation by real try-on


(a)


(b)

Figure 1-10 Garment fit evaluation by real try-on.

Traditional garment fit evaluation deals with both real and virtual try-on. In the aspect of real try-on, there are two frequently used methods for evaluating garment fit. One approach is the garment try-on with a physical mannequin (Figure 1-10(a)), in which a designer evaluates whether the garment is appropriate or not according to his/her experience. It is frequently used in the garment design processes. The other approach is the try-on with real human models (Figure 1-10(b)), in which the wearer directly evaluates the garment fit according to his/her feeling. It is frequently used in physical garment shops. As this method leads to more accurate evaluation results, designers sometimes also adopt it for evaluating garment fit in their design processes.

1.3.3 Garment fit evaluation by virtual try-on

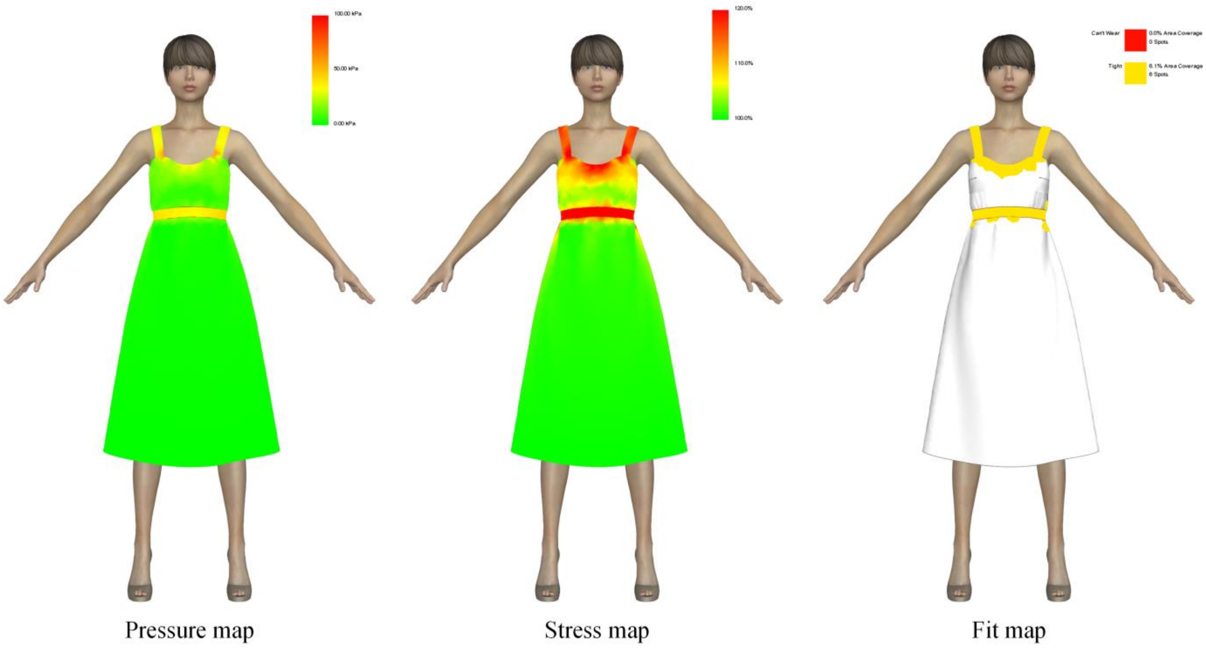


Figure 1-11 Garment fit evaluation by virtual try-on.

With the development of CAD and virtual reality technologies, the virtual garment try-on has been extensively proposed to evaluate garment fit in a design environment. This technology enables simulation of a garment making process and modeling of a 3D garment by using computerized 2D patterns, permitting to reduce the generation of real prototypes largely. A wearer can feel whether a garment is fit by real try-on; however, virtual try-on cannot [74]. Therefore, some supplementary means were proposed to evaluate garment fit of virtual try-on. At present, there are mainly two methods to do so. One approach is that the visual evaluation carried out on a 3D garment by fashion designers [32-33, 75]. In actual operation, some experienced designers use pressure maps, stress maps and fit maps generated by virtual try-on software for visual assessment of garment fit (Figure 1-11). However, these virtual try-on applications, strongly depend on mathematical models used in the 3D garment CAD software [47], cannot give high accurate garment fit evaluation related to real try-on. In practice, a human visual evaluation without direct contact with the real prototype is often considered as inaccurate and less convincing. The other approach is to measure the ease allowances or air layer thickness, which are between the human body and the garment [76-

77]. Then, evaluators analyze these measured indicators to evaluate garment fit based on their own empirical knowledge.

1.3.4 Discussion

Garment fit is influenced by fashion style, garment pattern [78], body shape [79-83, 63], body dimensions [2, 84], fabric material [85-86], and so on. The traditional garment fit evaluation uses ease allowance or air layer thickness to evaluate garment fit for avoiding real try-on. 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 a garment fits or not directly. However, the most important drawback of this method is that it requires real wearers to participate in the evaluation process and real prototype making. It is not necessarily available for garment design in a remote environment, which needs communications, collaborations and interactions between different professionals. In this context, the virtual garment try-on has more advantages than the classical real try-on, permitting interactions of designers and the concerned consumer around the virtual product display. Although there still exist some limitations in the virtual garment try-on related to uncertainty and imprecision on garment fitting, its development in the future will be very significant and conforms to the trends of classical industries towards connected factories. It should be further improved or optimized by integrating professional knowledge and experience of classical industries.

The emergence of artificial intelligence and machine learning technologies provides some 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 [87], such as, sensory evaluation of textile and related products [88-90, 75, 91], garment comfort prediction [92-93], intelligent systems of fashion design [94-99], garment production management [100-106, 98]; apparel retail [107-112], and apparel supply chain management [113-116]. Compared to the traditional methods, the 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. Due to these advantages of intelligent approaches, I propose to a machine learning-based method to evaluate garment fit. The corresponding work of machine learning-based garment fit evaluation technology (MLBGFET) has been expounded in Chapter 5.

1.4 Knowledge-based fashion design and fit evaluation

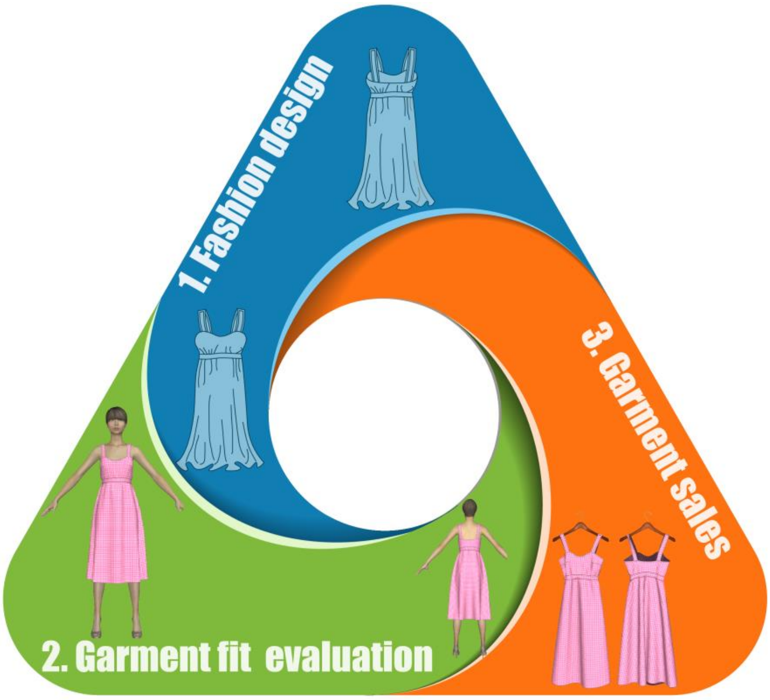


Figure 1-12 Relations between fashion design, garment fit evaluation, garment sales.

As shown in Figure 1-12, a garment needs to be evaluated fit in a fashion design process. According to the evaluation results, designers modify the garment. Only the garment meeting the requirements of fit evaluation criterion can be considered in the following production. After delivering a finished garment to the shop, it still needs to be evaluated fit by wearers. Customers only buy the garments with excellent fit. In the garment sale process, products in which fit and design are unsatisfied by customers will be returned to the design department. Based on the feedbacks of these problems, designers modify the garment designs again. The process repeats until the garment completely meets the customer’s requirements. Thus, it can be seen that garment design, fit evaluation and garment sale constitute, as three strongly interacted components, a unified system.

Currently, fashion design and fit evaluation are experience-based work. Fashion design and fit evaluation cannot be realized without the participation of designers having rich professional experience. However, it may take many years to train a designer to become excellent. This condition restricts the development of fashion companies. All fashion companies wish to extract and formalize the knowledge of fashion design and fit evaluation and exploit it freely, in order to guarantee a sustainable development of their fashion products and collections. Also, the extracted knowledge can be used by amateurs who do not master fashion design knowledge. This can help fashion companies to get rid of their dependence on specific designers and make the fashion product development process more efficient, more systematic and more adapted to personalized fit in the context of mass customization.

In my Ph.D. research, I propose a knowledge-based fashion design and fit evaluation system. This system includes four parts. The first part is GFPADT. By modeling the fashion design and pattern making knowledge, garment flat drawing and pattern making that belong to different departments, are integrated together. The second part is 3DIGPMT for realizing human computer interaction and computerized pattern making. In the process of human-computer interaction, the computer translates the whole work of pattern making work into several executable codes. Finally, pattern makers use a way of "what you see is what you get" to develop garment pattern for different body shapes and sizes with the help of 3DIPMT. The third part is MLBGFET, permitting to use a number of intelligent algorithms to construct fit evaluation models by learning from experimental data. Next, the proposed models can predict garment fit. The last part deals with applications of knowledge-based fashion design and fit evaluation. By integrating the previous three technological modules, I provide four feasible solutions for mass production, made-to-measure, mass customization and garment shopping online.

1.5 Conclusion

In this chapter, I introduced the state of the art of traditional fashion design, 3D fashion design and garment fit evaluation respectively. Then I discussed the shortcomings of present methods of fashion design and fit evaluation. Based on the previous researches, I proposed knowledge-based fashion design and fit evaluation to help garment enterprises develop and evaluate garment products rapidly and effectively. The knowledge-based fashion design and fit evaluation are the main content of this Ph.D. and are explained in more detail in the following sections.

CHAPTER 2: COMPUTATIONAL TOOLS FOR MODELING

In this chapter, I present the theoretical basis of the computational tools that are concerned in our approach. Through analyzing advantages and disadvantages of the computational tools, I choose some appropriate algorithms to model the relations between design requirements and design solutions; such as customers' personalized needs and garment patterns, clothing pressures requirements and garment fit perception. The tools of linear regression, Bayes classifier, decision trees and artificial neural networks, are applied to construct the mathematical models used in the proposed knowledge-based garment design and fit evaluation system.

2.1 Linear regression

A regression analysis is a statistical method for identifying the relation between a set of independent variables (inputs) and a dependent variable (output), under the hypothesis that this relation can be approximatively represented by a line. We call it simple linear regression analysis if there is only one independent variable. If two or more independents are included into a regression analysis; and independent variables and dependent variables have linear relations. We call it multiple linear regression analysis.

2.1.1 Simple linear regression

Let Y be an observable random variable, which subjects to a non-random variable x and a random error ε. Assuming that Y and x have the following linear relationship:

$$Y = \beta_0 + \beta_1 x + \varepsilon \qquad (2\text{-}1)$$

where random error ε's mean value $E(\varepsilon) = 0$ and variance $\mathrm{var}(\varepsilon) = \sigma^2 (\sigma > 0)$; regression coefficient β_0 and β_1 are fixed unknown parameters; Y and x are the dependent variable and free variable respectively.

Formula (2-1) is called a simple linear regression model.

For establishing a regression equation in practice, I first determine whether the linear regression model can be built, and then estimate the unknown model parameters β_0 and β_1. For this purpose, I perform n independent observations on the population (x, Y) to obtain n sets of data (called sample observations):

$$(x_1, y_1), (x_2, y_2), \cdots, (x_n, y_n)$$

then, a scatterplot is plotted in the Cartesian coordinate system $x0y$ according to the data points $(x_i, y_i), (i = 1, 2, \cdots, n)$. If the points $(x_i, y_i), (i = 1, 2, \cdots, n)$ are roughly close to a straight line or the scatterplot is in a linear shape, then the relationship between Y and x is considered to satisfy Formula (2-1). At this time, the least squares method can be used to obtain the estimations $\hat{\beta}_0$ and $\hat{\beta}_1$ of the regression model parameters β_0 and β_1, the estimated formula is:

$$\begin{cases} \hat{\beta}_0 = \bar{y} - \bar{x}\beta_1 \\ \hat{\beta}_1 = L_{xy}/L_{xx} \end{cases} \tag{2-2}$$

where $\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$; $\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$; $L_{xx} = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2$; $L_{xy} = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})$.

Finally, the empirical formula of a simple linear regression model is given as follows:

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x \tag{2-3}$$

The main task of a linear regression analysis is following. The first step is to use the sample observations in order to estimate the regression coefficients $\hat{\beta}_0$、$\hat{\beta}_1$ and σ; the second step enables to perform a test of significance on the linearity of Equation 2-3. If the linearity relation is validated, the third step is to make a prediction of Y for any given value $x = x_0$.

2.1.2 Multiple linear regression

Let Y be an observable random variable, which subjects to $p(P > 0)$ non-random variables $X_1, X_2, \cdots, X_p$ and a random error ε. If Y and $X_1, X_2, \cdots, X_p$ have the following linear relationship:

$$\mathrm{Y} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p + \varepsilon \tag{2-4}$$

where ε is a random variable, whose mean is 0 and variance is $\sigma^2(\sigma > 0)$, regression coefficients $\beta_0, \beta_1, \cdots, \beta_p$ are fixed unknown parameters; Y is a interpreted variable, $X_1, X_2, \cdots, X_p$ are explanatory variables, then formula (2-4) is called a multiple linear regression model.

By definition, in the multiple linear regression model (2-4), the independent variables $X_1, X_2, \cdots, X_p$ are non-random variable, whose values can be observed precisely; the random error ε represents the influence of other random factors on the dependent variable Y. The population $(X_1, X_2, \cdots, X_p; Y)$'s n group observations $(x_{i1}, x_{i2}, \cdots, x_{ip}; y_i)$ $(i = 1, 2, \cdots, n; n > p)$ should satisfy formula (2-4), that is,

$$\begin{cases} y_1 = \beta_0 + \beta_1 x_{11} + \beta_2 x_{12} + \cdots + \beta_p x_{1p} + \varepsilon_1 \\ y_2 = \beta_0 + \beta_1 x_{21} + \beta_2 x_{22} + \cdots + \beta_p x_{2p} + \varepsilon_2 \\ \cdots \\ y_n = \beta_0 + \beta_1 x_{n1} + \beta_2 x_{n2} + \cdots + \beta_p x_{np} + \varepsilon_n \end{cases} \tag{2-5}$$

where ε_1, ε_2, $\cdots$, ε_n are independent of each other and if let $\varepsilon_i \sim N(0, \sigma^2)(i = 1, 2, \cdots, n)$, $Y = \begin{Bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{Bmatrix}$, $X = \begin{Bmatrix} 1 & x_{11} & x_{12} & \cdots & x_{1p} \\ 1 & x_{21} & x_{22} & \cdots & x_{2p} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ 1 & x_{n1} & x_{n2} & \cdots & x_{np} \end{Bmatrix}$, $\beta = \begin{Bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_p \end{Bmatrix}$, $\varepsilon = \begin{Bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{Bmatrix}$

then, the multiple linear regression model (2-4) can be expressed as the following matrix:

$$Y = X\beta + \varepsilon_1 \tag{2-6}$$

where Y is an observation vector; X is a design matrix; β is an estimated vector; ε is an unobservable n-dimensional random vector, whose components are independent of each other; and assuming $\varepsilon_i \sim N(0, \sigma^2 I_n)$.

2.1.3 Discussion

Linear regression is the first type of regression analysis to be studied rigorously and to be used extensively in practical applications [117]. This is because models that depend linearly on their unknown parameters are easier to fit than nonlinear models and the statistical properties of the resulting estimators are easier to be determined.

Linear regression has been widely applied in different sectors. Most of its applications fall into one of the following broad categories:

1) If the goal of the study is prediction, forecasting or error reduction, linear regression can be used to fit a predictive model from an observed data set of Y and X values. After developing such a model, if a new value of X is given, the fitted model can be used to predict the value of Y.

2) Given a variable y and a number of variables $X_1, \ldots, X_p$ that may be related to Y, linear regression analysis can be applied to quantify the strength of the relationship between y and the X_j, to assess which X_j may have no relationship with Y at all, and to identify which subsets of the X_j contain redundant information about Y.

A linear model is simpler than a quadratic model and often works just as well for most purposes. Due to the advantages of multiple linear regressions, I select multiple linear regressions to construct the prediction models in Chapter 3 and 4.

2.2 Bayes classifier

In the statistics and computer science literature, Naive Bayes models are known under a variety of names, including simple Bayes and independence Bayes [118]. All these names reference the use of Bayes' theorem in the classifier's decision rule. Bayes classifier is a typical statistical classification method, which can give a probability that a sample belongs to a particular class. Bayes classifier is one of the methods to deal with uncertain knowledge inference problems. Bayes classifications mainly include Naive Bayes classification and Bayes networks. Bayes classification can be comparable with the decision trees and neural networks, and it is one of the better classifiers on learning efficiency and better classification performance. The applications of Bayes classification require the following two conditions: (1) the classification number is known; (2) the value distribution of the category attribute is known.

2.2.1 Bayes theorem

Definition 2.1 Let (Ω, F, P) be a probability space. If $A_i \subset \Omega (i = 1,2,\ldots,n)$, $A_i \cap A_j = \phi (i \neq j)$, and $\bigcup_{i=1}^{n} A_i = \Omega$, then $A_1, A_2, \ldots, A_n$ is called a finiteness part of Ω.

Theorem 2.1 Let (Ω, F, P) be a probability space. $A_2, \ldots A_n$ is a finiteness part of Ω, and $P(A_i) > 0$ $(i = 1,2,\ldots,n)$. For any event $B \in F$, there is:

$$P(B) = \sum_{i=1}^{n} P(B|A_i)\,P(A_i) \tag{2-7}$$

Theorem 2.2 Let (Ω, F, P) be a probability space. $A_2, \ldots A_n$ is a finiteness part of Ω, and $P(A_i) > 0$ $(i = 1,2,\ldots,n)$. For any event $B \in F$ and $P(B) > 0$, there is:

$$P(A_i|B) = \frac{P(B|A_i)P(A_i)}{\sum_{j=1}^{n} P(B|A_j)\,P(A_j)} \tag{2-8}$$

Formula (2-8) is called the Bayes formula.

2.2.2 Naive Bayes classifiers

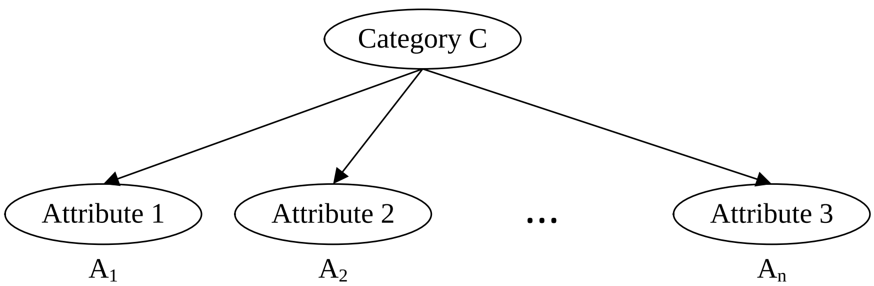


Figure 2-1 Naive Bayes classifiers.

In machine learning, Naive Bayes classifiers are a family of simple probabilistic classifiers based on the application of Bayes' theorem with strong (naive) independence assumptions between the features. A Naive Bayes classifier is the simplest classifier of the probability classifiers. As shown in Figure 2-1, Naive Bayes classifier is a dendriform Bayes network including a root node and a number of leaf points. Leaf points A_1, A_2, ... A_n are attribute variable, which describes the properties of the object to be classified. Root node C is a class variable, which describes the type of object.

A Naive Bayes classifier is based on the assumption of conditional independence: each attribute variable A_i is independent of each other under the condition of a given class variable C. This hypothesis makes the Naive Bias classifier have a relatively simple structure, and reduces the complexity of the construction of Bias network significantly. When satisfying the hypothesis, Naive Bayes has higher classification accuracy than the other classification methods. Given training set $D = \{d_1, d_2, \dots, d_m\}$, the ith training sample $d_i = (a_{il}, \dots, a_{in}, c_i)$, $\mathrm{a}_{il}, \dots, \mathrm{a}_{in}$ are the values of n attribute variables of the ith training sample, c_i is the value of class variable of the ith training sample. The classification process of the Naive Bias classifier is given as follows:

<u>Step 1:</u> The structure of Naive Bayes is constructed by taking the class variables as the root nodes of other variables.

<u>Step 2:</u> Calculate parametric table based on the known structure and training set D.

<u>Step 3:</u> Calculate posterior probability of the sample $(a_1, a_2, \dots, a_n)$ to be classified.

$$P(c^j|a) = \frac{P(c^j|a) \cdot P(c^j)}{P(a)} = \alpha \cdot P(c^j) \cdot \prod_{i=1}^{n} P(a_1|c^j)$$

where α is a constant called normal factor. c^j is the value of the class variable C. The unclassified sample $(a_1, a_2, \dots, a_n)$ is classified into the arg max $P(c^j|a)$ finally.

2.2.3 Discussion

The advantages of Naive Bayes are given below.

1) A Naive Bayes model has a solid mathematical foundation, as well as the stability of the classification efficiency.

2) The estimated parameters required by a Naive Bayes model are few, less sensitive to missing data, and the algorithm is relatively simple.

3) A Naive Bayes model has very high classification accuracy in many cases.

Due to the advantages of Naive Bayes, I select the Naive Bayes classifier as one of the three algorithms to construct garment fit evaluation models (see Chapter 5).

2.3 Decision Trees

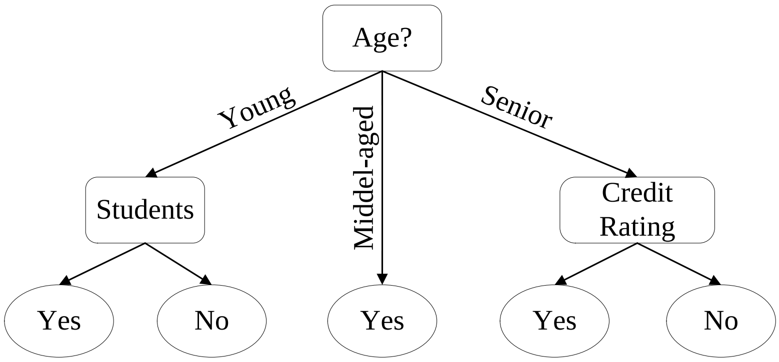


Figure 2-2 One example of a decision tree.

A decision tree is a tree structure that is similar to a binary tree or multi-tree. Each non-leaf node (including the root node) in the tree corresponds to a non-class attribute test in the training sample set. Each branch of non-leaf nodes corresponds to an attribute's test result. Each leaf node represents a class or class distribution. A path from the root node to the leaf node forms a classification rule. Decision trees can be easily translated into classification rules, and it is a very intuitive representation of classification model. As shown in Figure 2-2 [119], a decision node (e.g., age) has either two or more than two branches (e.g., youth, middle- aged and senior). Leaf node (e.g., yes or no) depicts a decision or a classification. The root node is the topmost decision node in a tree that is the best predictor. Decision trees can handle both numerical and categorical data. I introduce decision tree with ID3 and C4.5 algorithms respectively in the following sections.

2.3.1 Decision tree ID 3[120]

Iterative Dichotomiser 3 (ID3) is one of the earliest ideas of decision tree induction [121-122]. Its split criterion was founded on information theory. The most serious drawback of ID3 is the requirement that the data description may include only discrete features. When the original data table contains numerical features, they must be first discretized. The success of data mining processes consisting of data discretization and final model creation usually depends on the former part more than on the latter. Therefore, estimation of the efficiency and accuracy of ID3 in application to continuous data does not make much sense, because with one discretization method the results may be very good and with another one-completely wrong.

Denoting the purity criterion as I, we get the following formula of purity gain (impurity reduction):

$$\Delta I(s,D)=I(D)-\sum_{i=1}^{k}\frac{|D_i|}{|D|}I(D_i) \tag{2-9}$$

where s is the split, D is the dataset to be split and $I(D)=(D_1,\dots,D_k)$. Given the index I, the best splits of dataset D are those maximizing $\Delta I(s,D)$.

The method is a typical example of top-down recursive induction presented in Algorithm 2.1. Split qualities are estimated with the purity gain criterion (2-9) using entropy as node impurity measure:

$$I_E(D)=H_c(D)=-\sum_{c\in\xi}P(c|D)\log_2 P(c|D) \tag{2-10}$$

Such combination of formulae (entropy reduction) is called Information Gain (IG) criterion:

$$IG(s,D)=\Delta I_E(s,D) \tag{2-11}$$

In practice, the probabilities of classes within the node N are usually estimated by ratios $\frac{n_c}{n}$ of the numbers of objects in node N data representing class c and the numbers of all objects falling into N. When implementing the information gain criterion for the sake of decision tree induction, one usually simplifies the formulae. Converting expressions according to the equality

$$-\sum_{c\in\xi}P(c|D)\log_2 P(c|D)=\log n-\frac{1}{n}\sum_{c\in\xi}n_c\log n_c,$$

the information gain resulting from the split of $\boldsymbol{N}$ into parts $\boldsymbol{N^p}$ can be written as

$$IG=\log n+\frac{1}{n}\left(-\sum_{c\in\xi}n_c\log n_c-\sum_{p}n^p\log n^p+\sum_{p}\sum_{c}n_c^p\log n_c^p\right) \tag{2-12}$$

Because in decision tree induction we are interested in comparison between splits, not in precise calculation of IG, the constant parts of the formula given above can be ignored, and only the second and third components in the big parentheses need to be calculated.

In each step of ID3 algorithm, a node is split into as many subnodes as the number of possible values of the feature used for the split. The exhaustive search for best split, in this case, just estimates the quality of each feature, because only one split is possible per feature. The feature offering maximal entropy reduction is selected, the node split, and the feature used for the split is removed from the data passed down to the subnodes, because it is no longer useful in the tree branch (all objects have the same value of this feature).

An important disadvantage of such split technique is that the features with many possible values are preferred over those with small counts of symbols, even when the former are not too valuable—in an extreme case, if each object has a unique value of a feature, the feature will reduce the entropy to zero, so will be treated as very precious, while in fact, its value is overestimated due to the split into many nodes with single data objects.

Apart from the main ID3 algorithm, Quinlan has presented some other interesting contributions [121]. One of them is the method for fastening decision tree induction when training dataset is very large. Quinlan proposed an iterative framework discussed also by O'Keefe [123]. It is based on using a window—a subset of the training dataset instead of all training objects. In such approach, ID3 may need a number of tree induction iterations to provide final classification tree. The process starts with building a tree to classify objects in the window with maximum accuracy. Then, the tree classifies the objects outside the window. If all the objects are classified correctly, the tree is the final result. Otherwise, a selection of incorrectly classified objects is added to the window and next tree is generated. If the window is allowed to grow to the size capable of containing all training data objects, the process is guaranteed to end up with a maximally accurate tree (with respect to the training data). If not, some problems with convergence may also occur.

2.3.2 Decision tree C4.5[120]

Another very popular decision tree induction system is decision tree with C4.5 algorithm by Quinlan [124]. It has found numerous applications. The system arose from ID3 and shares many solutions with its ancestor. Main differences introduced in C4.5 are: 1) Modified node impurity measure; 2) Support for direct handling continuous attributes (no necessity to discretize them); 3) Introduction of a pruning method; 4) Precise methods for handling data with missing values.

(1) Impurity Measure

Modified measure of node impurity aimed at eliminating bias in split feature selection, that is, favoring features with many possible values by the information gain criterion used in ID3. To replace the IG, Quinlan [124] proposed information gain ratio (IGR) defined as

$$\Delta I(s,D) = \frac{\Delta I_E(s,D)}{SI(s,D)}, \tag{2-13}$$

where split information $SI(s, D)$ is the entropy of the split $S(D) = (D_1, \dots, D_n)$:

$$SI(s, D) = -\sum_i p_i \log_2 p_i \,, \left(p_i = \frac{|D_i|}{|D|}\right) \tag{2-14}$$

(2) Handling Continuous Attributes

All sensible binary splits, deduced from the training data, are examined and the one with the best score (here the largest information gain ratio) chosen. Unlike symbolic features, continuous attributes may occur at different levels of the same tree many times (symbolic ones, when used in the tree, are no longer useful and because of that are not considered in further splits in the branch).

(3) Decision tree Pruning

In ID3 a statistical test of independence served as a stop criterion to prevent oversized trees, overfitting the training data. Decision tree C4.5 offers another technique of generalization control. It builds (almost) maximally accurate trees and then prunes them to get rid of too detailed nodes that have not learned any general classification rule but just adjusted to specific data objects present in the training sample. The word "almost" added in parenthesis reflects what can be found in the source code of decision tree C4.5 about the process of tree construction: decision tree C4.5 has a parameter MINOBJS, which controls a pre-pruning method. If a node to be split contains a too small number of objects or the split would generate too small nodes, further splits are rejected. After the tree is constructed, each node is tested with a statistical tool to estimate the probability that the node split causes error reduction (assuming binomial distribution of erroneous decisions). Each node, for which the probability is below a given threshold, is pruned or the subtree rooted in the node is replaced by its best subtree (the technique was named grafting).

(4) Handling Missing Values

Objects with missing values can also be used in both the process of decision tree C4.5 construction and in further classification with a ready tree. At the stage of tree construction, in calculation of IGR, the objects with missing values of the feature being analyzed are ignored—the index is computed for a reduced set of objects and the result is scaled by the factor of probability of value accessibility (estimated by the fraction of the number of objects with non-missing value of the feature and the number of all training objects at the node).When the training data sample is split for subnodes creation, weights are introduced to reflect that it is not certain which path should be followed by the training data objects with missing decision feature values. The weights may be interpreted as the probabilities of meeting or not the condition assigned to the node. They are calculated as the proportions reflecting the distribution of other data (with non-missing value) among the subnodes. When the weights are introduced, they must be considered also in further calculations of the IGR—wherever cardinalities are used (see Formulas (2-9), (2-13) and (2-14), sums of the weights are calculated instead of just the numbers of elements (naturally, the default initial weight value for each object is 1). Similarly, at classification stage, if a decision feature value is missing for a data object, all subnodes are tested and decisions obtained from each path are combined by adequate weighting to obtain final probabilities of the classes for the object.

2.3.3 Discussion

Decision trees have many advantages, which can be summarized as follows. 1) A decision tree is easy to be understood and realized. It does not require the user to master a lot of background knowledge. It can directly reflect the characteristics of the data and relations between different attributes by IF…THEN rules. 2) For building a decision tree, data preparation is very simple. It can deal with numerical data and linguistic data in the same time.

Compared to ID 3, the advantages of decision tree with C4.5 algorithm can be described as follows. 1) Decision tree with C4.5 can accept both continuous and discrete features; 2) C4.5 handles incomplete data; 3) C4.5 can solve the over-fitting problem by the bottom-up technique, usually known as "pruning".

Based on the above analysis, I select a decision tree with C4.5 algorithm to build the garment fit evaluation model (see Chapter 5).

2.4 Artificial Neural Networks

2.4.1 Basic principle

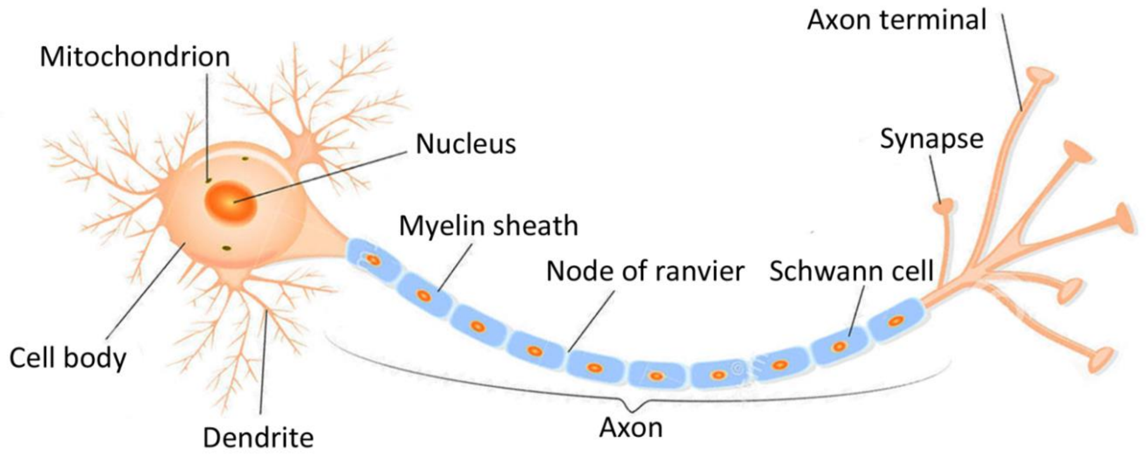


Figure 2-3 Biological neuron structure.

Neural networks are considered as a prominent component of futuristic artificial intelligence. Currently, the phrase neural networks are synonymous with artificial neural networks whose working concept is similar to that of human nervous system, and hence the name.

Figure 2-3 shows the structure of a biological neuron. Our brains use extremely large interconnected networks of neurons to process information and model the world we live in. Electrical inputs are passed through this network of neurons, which result in an output being produced. In the case of a biological brain, this could result in contracting a muscle or signaling your sweat glands to produce sweat. A neuron collects inputs using a structure called dendrites, the neuron effectively sums all of these inputs from the dendrites and if the resulting value is greater than its firing threshold, the neuron fires. When the neuron fires it sends an electrical impulse through the neuron's axon to its boutons, these boutons can then be networked to thousands of other neurons via connections called synapses. There are about one hundred billion (100,000,000,000) neurons inside the human brain each with about one thousand synaptic connections. It is effectively the way in which these synapses are wired that give our brains the ability to process information the way they do.

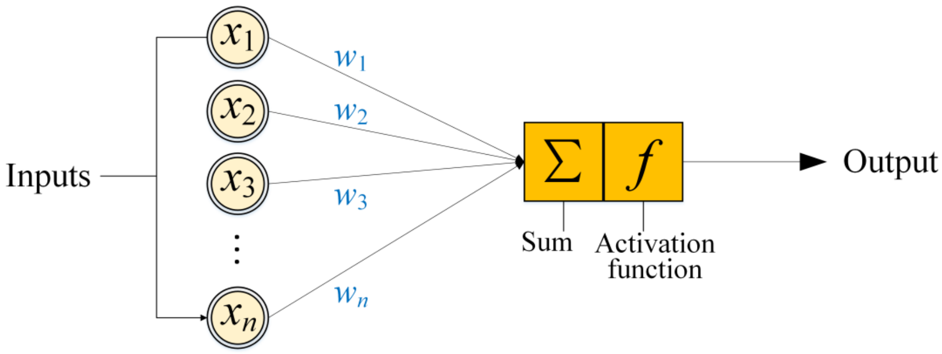


Figure 2-4 Perceptron's structure.

Artificial neuron models are at their core-simplified models based on biological neurons. This allows them to capture the essence of how a biological neuron functions. We usually refer to these artificial neurons as "perceptrons". As shown in Figure 2-4, a typical perceptron will have many inputs and these inputs are all individually weighted. The perceptron weights can either amplify or deamplify the original input signal. For example, if the input is "1" and the input's weight is "0.2" the input will be decreased to "0.2". These weighted signals are then added together and passed into the activation function. The activation function is used to convert the input into a more useful output. There are many different types of activation function but one of the simplest would be step function (Figure 2-5). A step function will typically output a "1" if the input is higher than a certain threshold; otherwise, its output will be "0".

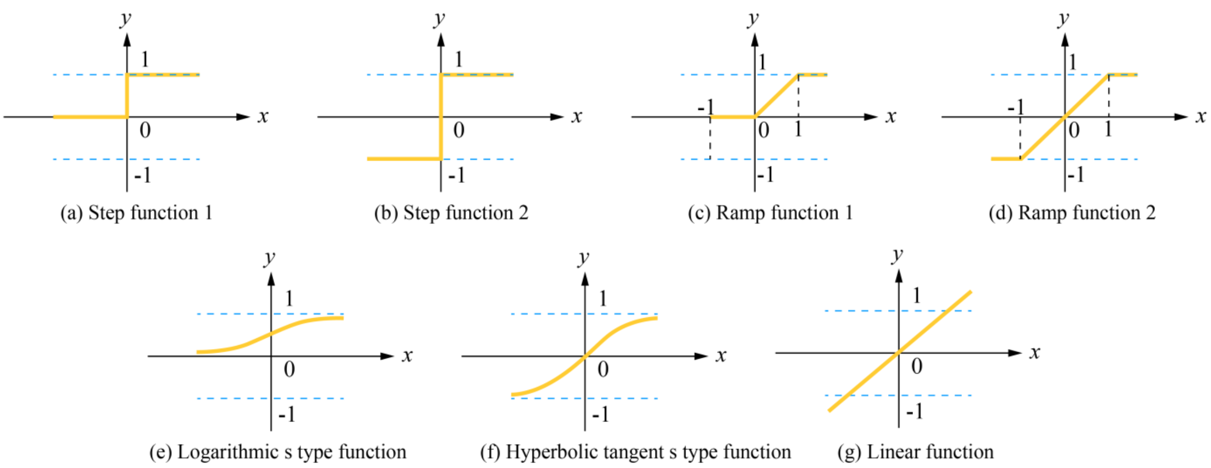


Figure 2-5 Activation functions.

One of the most impressive features of artificial neural networks is their ability to learn. We know that artificial neural networks are inspired by the biological nervous system, in particular, the human brain. One of the most interesting characteristics of the human brain is its ability to learn. There are many different algorithms that can be used when training artificial neural networks, each with their own separate advantages and disadvantages. The learning process within artificial neural networks is a result of altering the network's weights, with some kind of learning algorithm. The three major learning paradigms are instructed, as follows.

(1) Supervised Learning

The learning algorithm would fall under this category if the desired output for the network is also provided with the input while training the network. By providing the neural network with both an input and output pair it is possible to calculate an error based on its target output and actual output. It can then use that error to make corrections to the network by updating its weights.

(2) Unsupervised Learning

In this paradigm, the neural network is only given a set of inputs and it is the neural network's responsibility to find some kind of pattern within the inputs provided without any external aid. This type of learning paradigm is often used in data mining and is also used by many recommendation algorithms due to their ability to predict a user's preferences based on the preferences of other similar users it has grouped together.

(3) Reinforcement Learning

Reinforcement learning is similar to supervised learning in that some feedback is given; however, instead of providing a target output a reward is given based on how well the system performed. The aim of reinforcement learning is to maximize the reward the system receives through trial-and-error. This paradigm relates strongly with how learning works in nature, for example an animal might remember the actions it's previously taken which helped it to find food (the reward).

After learning from data, artificialneural networks carry out classification, prediction, etc.

2.4.2 Back Propagation Artificial Neural Networks

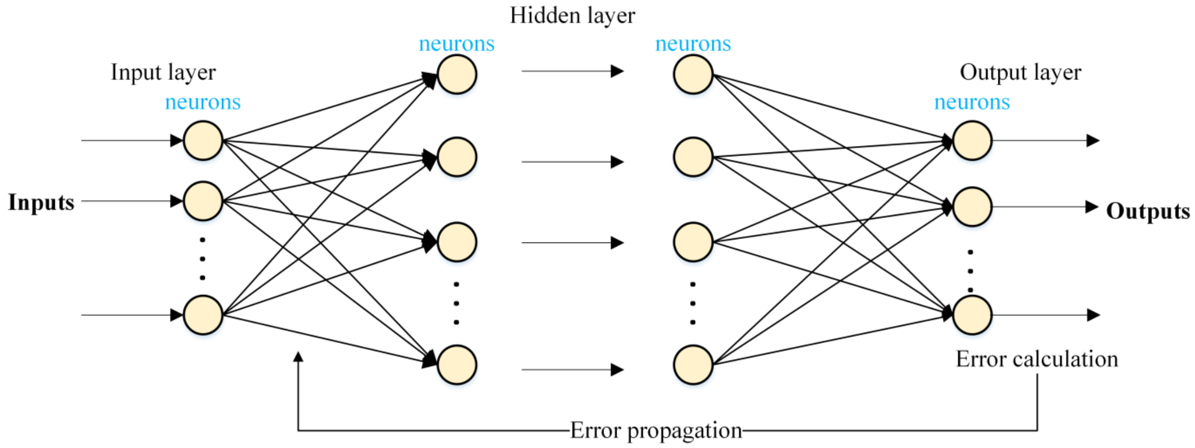


Figure 2-6 BP network structure.

Back Propagation Artificial Neural Networks (BP-ANN) is a supervised learning algorithm for feedforward neural networks. The network does not need feedback. After initializing the weights of the neurons with random values between two values, the network is capable to adjust the weights automatically using a two-phase algorithm:

Frist, forward propagation of a training pattern's input through the neural network to activate the neurons and get the network outputs;

Second, back propagation from the outputs node to the inner ones in which phase the network previous outputs are compared with the expected outputs from the training patterns, an error estimation is computed and back propagated in order to adjust neurons weights.

A BP-ANN has an input layer, one or more hidden layers and an output layer (Figure 2-6). A neuron is an entity that copies the human brain neuron. It responds to a given input based on the activation function and weights. If the activation function's output is greater than a threshold, the neuron is excited (it produces an output). The number of neurons in each layer can be adapted to meet the requirements. In order to be considered valid, the neuron's activation function must be differentiable. Being a gradient descent method, it minimizes the total squared error of the output computed by the net. The aim is to train the network to achieve a balance between the ability to respond correctly to the input patterns that are used for training and the ability to provide a good response to the inputs that are similar.

The main steps for training a network include hidden neuron's output calculation, output layer's output calculation, output and hidden layers' errors calculation, and weight adjustment. A hidden neuron's (neuron on a hidden layer) output h_j is calculated using the next formula:

$$h_j = f\left(\sum_{i=1}^{A} w_{hij} x_i - \theta_j\right), \ j = 1, 2, \cdots, B$$

where x_i is the network input; w_{oij}'s are the weights on the hidden layer; θ_j is the activation function threshold; A the inputs number and B the hidden neurons number.

The output layer results y_j are calculated using this formula:

$$y_j = f\left(\sum_{i=1}^{B} w_{oij} h_i - \theta_j\right), \ j = 1, 2, \cdots, C$$

where h_i is calculated before and C is the output layer's neurons number; w_{oij} is the weight on the output layer.

The output layer error δ_{oj} and for the hidden layer error δ_{hj} are computed with:

$$\delta_{oj} = y_j(1 - y_j)(d_j - y_j), \ j = 1, 2, \cdots, C$$

$$\delta_{hj} = h_j(1 - h_j)\sum_{i=1}^{C} w_{hij}\delta_{oi}, \ j = 1, 2, \cdots, B$$

where d_j is the network expected output.

The weights for the next step are adjusted as follow:

$$w_{oij}(t+1) = \eta\delta_{oj}h_j + w_{oij}(t), \ i = 1, 2, \cdots, B, j = 1, 2, \cdots, C$$

$$w_{hij}(t+1) = \eta\delta_{hj}x_i + w_{hij}(t), \ i = 1, 2, \cdots, A, j = 1, 2, \cdots, B$$

where η is the learning rate.

According to the previous steps, I adjust the weights until BP-ANN's outputs meet requirements. I think that the weights represent the knowledge of the neural network. After learning from data (weights adjustment process), the BP-ANN algorithm performs the output calculation according to the adjusted weights and inputs.

2.4.3 Discussion

Currently, artificial neural networks have become a very famous topic of interest. In recent years, they have been applied in almost all the industrial fields for solving a wide range of technical and management problems in an easier and convenient way [125]. Eighty percent applications of artificial neural networks adopt the BP-ANN algorithm. Compared with the other learning algorithms; the advantages of BP-ANN can be summarized as follows:

1) Nonlinear mapping ability: actually, a BP-ANN can realize a mapping function, from its input to its output. It has been proved that a three layer neural network is capable of approximating any nonlinear continuous function with arbitrary precision [126]. It is especially suitable for modeling the complex internal mechanism of a nonlinear system.

2) Self-learning and adaptive ability: by learning from experimental data, a BP-ANN can automatically adjust the concerned parameters of the model so that the overall errors of the model outputs related to real outputs can be minimized.

3) Generalization ability: the so-called generalization ability refers to that pattern classifier design not only assures the required classification object having correctly classification, but also cares whether the network carries out a correct classification for unknown patterns or noise pollution patterns after network training. In other words, BP neural networks have the ability to apply learning outcomes to new knowledge.

4) Tolerance ability: global training results of BP-ANN do not cause a great impact when some neurons are destroyed. The BP-ANN system can still work normally, even if the network has local damage. That is to say, BP neural networks have a certain fault-tolerant capability.

Due to the advantages of BP-ANN, I select BP-ANN as the one of the three algorithms to construct garment fit evaluation models in Chapter 5.

2.5 Conclusion

In this chapter, I introduced the theories of linear regression, Bayes classifier, artificial neural networks and decision trees respectively. Based on the analysis of these algorithms' advantages and disadvantages, linear regression is adopted to construct parametric fashion design models in Chapter 3 and fabric elastic model in Chapter 4; Naive Bayes classifiers, decision tree with C4.5 and BP-ANN are selected to construct garment fit evaluation models in Chapter 5.

CHAPTER 3: GARMENT FLAT AND PATTERN ASSOCIATED DESIGN TECHNOLOGY

In this chapter, I propose a Garment Flat and Pattern Associate Design Technology (GFPADT) in order to combine garment flat drawing and pattern making together by using a number of common parameters through a parametric design process. Based on this technology, a software system has been developed. In this system, by inputting the body dimensions of a specific consumer and his/her desired garment style, the garment's flats and the corresponding patterns can be generated rapidly and automatically. This technology can be applied for realizing mass customization, mass production in fashion companies in order to improve the working efficiency of all designers.

3.1 General scheme

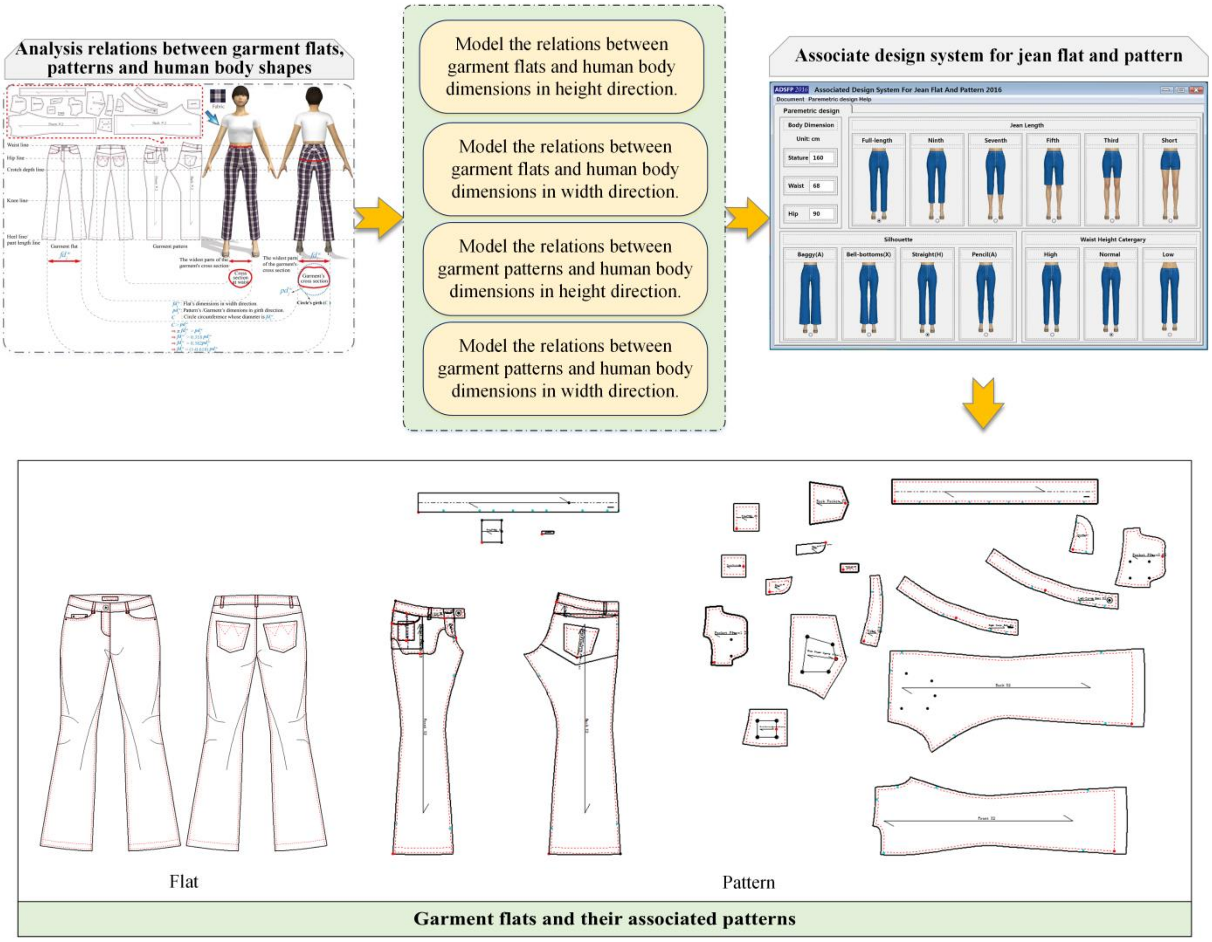


Figure 3-1 General scheme of GFPADT.

The general scheme of GFPADT is described in Figure 3-1. The main idea is to develop four mathematical models characterizing the relations of human body shapes with garment flats and garments patterns respectively, and then set up the relation between flats and patterns from these models. The corresponding details are given below. (Note: all the virtual try-on figures were generated by CLO 3D software.)

3.2 Methodology

3.2.1 Relationship between garment flats, patterns and human body shapes

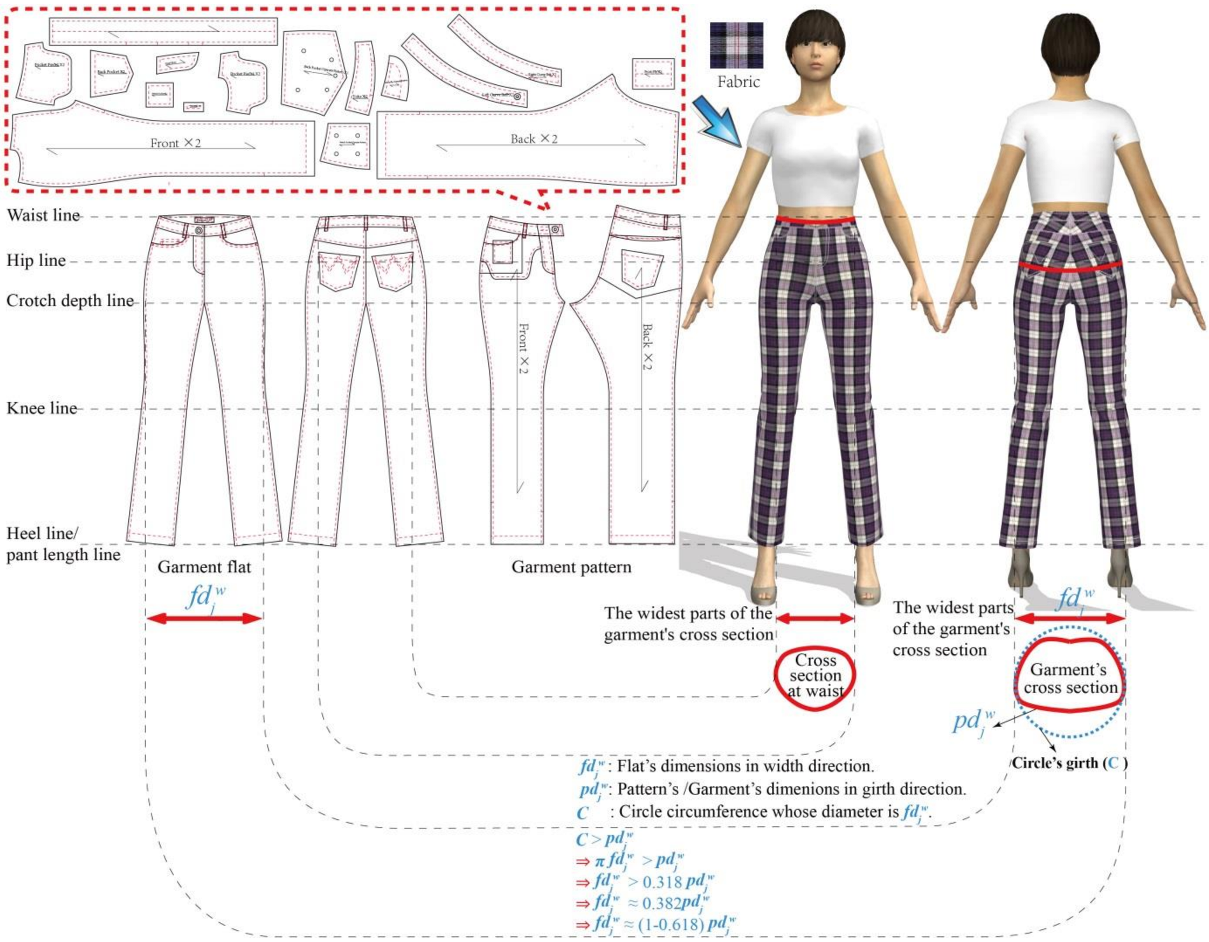


Figure 3-2 Relationship between flats, patterns and the human body shapes.

Traditional pattern making methods are based on body dimensions [21]. However, traditional garment flat drawing methods utilize garment proportions instead of body dimensions. In this chapter, I wish to identify the relation between flat drawing and pattern making by studying the relations of human body dimensions with garment flats and garment patterns respectively. Here, body dimensions are taken as an intermediate attribute linking the previous two design spaces (flat design and pattern design). Compared with the traditional methods, permitting to make garment flat drawing and pattern making separately, the proposed design method is a completely original.

In general, that human body dimensions are mainly divided into two categories: height and width directions [127, 21], the same for the dimensions of garment flats and patterns. As shown in Figure 3-2, the garment flats and their associated patterns share the common waistline, hip line, crotch depth line, knee line and pant length line. In the height direction, dimensions of garment flats and their associated patterns have one-to-one relationships (Figure 3-2). As garment patterns' dimensions in height are calculated according to the corresponding human body dimensions (a customer or a standard size), garment flats' dimensions can also be calculated in the same way. Likewise, in the width direction, the widest dimension of a garment's cross-section is equal to that of on the garment flat at the same position (Figure 3-2). The above analysis shows that garment flats, garment patterns and human body shapes are closely correlated. The dimensions of garment flats and patterns can be represented by human body dimensions. In other words, flats and the corresponding patterns can be drawn together based on human body dimensions. This is the basic principle of GFPADT.

3.2.2 Modeling the relationship between garment flats, patterns and human body shapes

According to the above analysis, I construct four parametric models characterizing the relations between garment flats, patterns and human body shapes.

(1) Concepts formalization

The concepts involved in this study are formalized as follows:

Let fd_i^h and pd_i^h be the height dimensions of the flat and its associated pattern at the ith position respectively ($i = 1, 2, \ldots, n$).

Let fd_j^w and pd_j^w be the width dimensions of the flat and its associated pattern at the jth position respectively ($j = 1, 2, \ldots, m$).

Let bd_i^h be the height body dimension at the ith position (ex. waist height, hip height, stature).

Let bd_j^w be the width body dimension at the jth position (ex. waist girth, hip girth).

Let kbd_x^h be the key height dimension, which is found at the xth position ($x \in \{1,2, \ldots, n\}$}) and with which the other height dimensions are associated (ex. stature is a key dimension for trousers). It is included in the set of $\{bd_i^h|\ i = 1, \ldots, n\}$ and varies with the desired garment style.

Let kbd_y^w be the key width dimension, which is found at the yth position ($y \in \{1,2\ \ldots, m\}$) and with which the other height dimensions are associated (ex. hip girth for trousers). It is included in the set of $\{bd_j^w|j = 1, \ldots, m\}$ and varies with the desired garment style.

Let e_j^w be the ease allowance of the garment at the jth position.

Let n be the number of dimensions in the height direction required for both garment flat drawing and pattern making.

Let m be the number of dimensions in the width direction required for garment flat drawing and pattern making;

Let k be the number of key dimensions of the human body in the height direction.

Let s be the number of key dimensions of the human body in the width direction.

I suppose that for a specific design, I have identified k key height dimensions at different positions $i_1, i_2, \cdots, i_k$. Now I define n functions, denoted as $f_i(.)$, characterizing the relations of these k key dimensions $kbd_{i_1}^h$, $kbd_{i_2}^h$, … , $kbd_{i_k}^h$ with all height dimensions bd_i^h. I have $bd_i^h = f_i\left(kbd_{i_1}^h, kbd_{i_2}^h, , \ldots, kbd_{i_k}^h\right)$ with $i \in \{1, \ldots, n\}$.

According to the same idea, I have identified s key height dimensions at different positions $j_1, j_2, \cdots, j_s$. Now I define m functions, denoted as $g_j(.)$, characterizing the relations of these s key dimensions $kbd_{j_1}^w$, $kbd_{j_2}^w$, … , $kbd_{j_s}^w$ with all width dimensions bd_j^w. I have $bd_i^w = g_j\left(kbd_{j_1}^w, kbd_{j_2}^w, , \ldots, kbd_{j_s}^w\right)$ with $j \in \{1, \ldots, m\}$.

(2) Modeling the relations between garment flats and patterns

The relations between a flat and its associated patterns for all the height dimensions are given below.

$$fd_i^h = pd_i^h, (i = 1,2, \ldots, n) \tag{3-1}$$

The relations between a flat and its associated patterns in the width direction are as follows:

$$fd_j^w = (1 - 0.618)pd_j^w, (j = 1,2, \ldots, m) \tag{3-2}$$

The derivation of fd_j^w is shown in Figure 3-2, and fd_j^w is deduced as follows: Let C be the perimeter of a circle whose diameter is fd_j^w. In general, its associated pattern is designed to be the maximal closed surface inside this circle (see Figure 3-2). According to our common knowledge, I have $C > fd_j^w$ leading to the following inequalities:

$$\pi fd_j^w > pd_j^w \Rightarrow fd_j^w > pd_j^w/\pi \Rightarrow fd_j^w > 0.318pd_j^w$$

Next, from this inequality, I try to define a linear relation between fd_j^w and pd_j^w by replacing the coefficient 0.318 by a larger value 0.382. I have

$fd_j^w = 0.382pd_j^w$, leading to $fd_j^w = (1 - 0.618)pd_j^w$.

The replacement of 0.318 by 0.382 is for two reasons. The first is that the circle perimeter C is just slightly larger than the expected garment girth at the same position (Figure 3-2). Therefore, fd_j^w should be set to be larger than $0.318pd_j^w$ in order to maintain this inequality. The second reason is that the golden ratio (0.618 or 0.382) is widely applied in the fashion design processes [128-129] as an acceptable beauty proportion.

(3) Modeling relationship between garment patterns and body dimensions

The relations between garment patterns and body dimensions in the height direction are given as follows:

$$pd_i^h = bd_i^h, (j = 1,2, \ldots, n) \tag{3-3}$$

The relations between garment patterns and body dimensions in the width direction are as follows:

$$pd_j^w = bd_j^w + e_j^w, (j = 1,2, \ldots, m) \tag{3-4}$$

(4) Modeling relations between key body dimensions and any other ones

The relations between key body dimensions and any others in the height direction have been defined in the part of (1). I remind:

$$bd_i^h = f_i\left(kbd_{i_1}^h, kbd_{i_2}^h, , \ldots , kbd_{i_k}^h\right), (i = 1,2, \ldots, n; 1 \leq k \leq n) \tag{3-5}$$

The same for the relations between key body dimensions and any others in the width direction:

$$bd_j^w = g_j\left(kbd_{j_1}^w, kbd_{j_2}^w, \ldots, kbd_{j_s}^w\right), (j = 1,2, \ldots, m; 1 \leq s \leq m) \tag{3-6}$$

(5) Modeling relationships between garment flats, patterns and the human body shape

According to Formulas (3-1), (3-3) and (3-5), the relations between garment flats and human body dimensions, between patterns and the human body dimensions in the height direction are given below.

$$fd_i^h = f_i\left(kbd_{i_1}^h, kbd_{i_2}^h, , \ldots , kbd_{i_k}^h\right), (i = 1,2, \ldots, n; 1 \leq k \leq n) \tag{3-7}$$

$$pd_i^h = f_i\left(kbd_{i_1}^h, kbd_{i_2}^h, , \dots, kbd_{i_k}^h\right), (i = 1,2, \dots, n; 1 \le k \le n) \quad (3\text{-}8)$$

According to Formulas (3-2)，(3-4) and (3-6), the relations between garment flats and human body dimensions, between patterns and body dimensions in the width direction is as follows:

$$fd_j^w = (1 - 0.618)\left\{g_j\left(kbd_{j_1}^w, kbd_{j_2}^w, \dots, kbd_{j_s}^w\right) + e_j^w\right\}, (j = 1,2, \dots, m; 1 \le s \le m) \quad (3\text{-}9)$$

$$pd_j^w = g_j\left(kbd_{j_1}^w, kbd_{j_2}^w, \dots, kbd_{j_s}^w\right) + e_j^w, (j = 1,2, \dots, m; 1 \le s \le m) \quad (3\text{-}10)$$

Evidently, all the dimensions of garment flats and their associated patterns in height and width directions can be easily calculated from the corresponding key body dimensions according to Formulas (3-7), (3-8), (3-9) and (3-10).

3.3 Example of application

I select a jean style to test and validate the proposed method. Our selection is based on the fact that jeans are very popular all over the world. The proposed method can also be applied to other garment styles.

3.3.1 Anthropometric data acquisition and processing

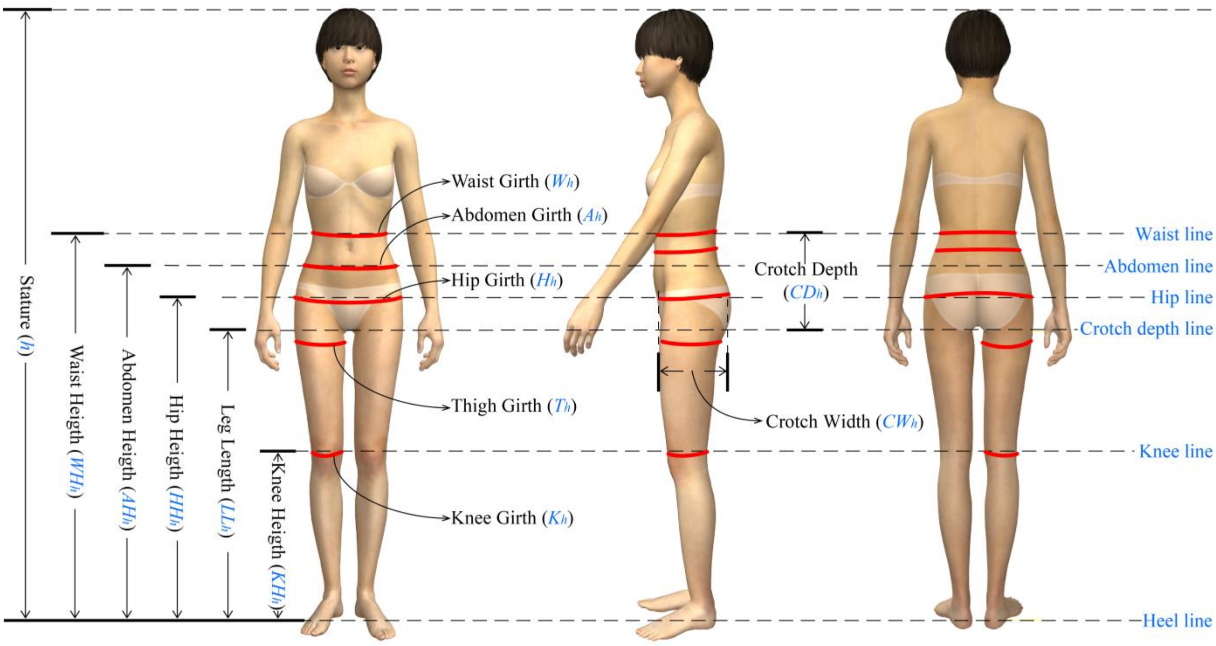


Figure 3-3 Legend of measurement dimensions.

(1) Anthropometric data acquisition

I randomly select 116 young women aged 20-30 years old from the Northeast of China. Their heights vary from 145 cm to 180 cm. A 3D body scanner (Vitus Smart), which has been widely applied in different human body characterization scenarios [130-131], is used to measure and extract body dimensions. This 3D body scanner automatically extracts dozens of body dimensions from each subject. According to designer's knowledge, I only choose 13 body measurements (See Figure 3-3), for characterizing lower body shapes. The sample size is calculated according to Formula (3-11) at 95% confidence interval, for the 5th and 95th percentiles [132].

$$N \geq 1.96^2 \times MAX({CV_i}^2)/A^2 \tag{3-11}$$

where N is the minimum number of sample size; CV_i the coefficient of variation for each measuring item i, and A the relatively permissible error. Considering that this study is a common scientific research project, I set the value of "A" to 1.6%. Finally, I calculate the sample size "N", with a target value of at least 100. Considering the existence of some invalid samples and special body types, 116 young women are selected ultimately.

(2) Data preprocessing

Table 3-1 Anthropometric data (unit: cm)

No.	h	LL_h	WH_h	HH_h	AH_h	KH_h	H_h	W_h	CD_h	CW_h	A_h	T_h	K_h
1	168.9	72.9	105.0	87.2	99.2	46.6	100.3	68.3	32.2	20.3	83.7	56.5	37.4
2	167.4	74.1	104.5	87.5	96.5	44.7	98.8	67.0	30.5	19.5	84.5	57.5	39.4
3	161.9	69.8	99.5	80.9	93.4	44.5	94.3	64.5	29.7	19.8	77.8	53.0	36.2
4	167.4	76.0	105.2	88.6	98.2	46.4	100.8	71.1	29.3	20.1	85.3	58.9	40.8
5	168.9	70.5	105.5	85.8	97.8	44.3	101.8	73.0	35.1	20.2	79.4	59.0	38.5
6	166.6	72.9	106.7	87.6	100.1	46.6	92.9	64.5	33.8	19.6	79.1	51.8	38.6
7	171.4	75.2	107.9	90.1	100.9	47.2	101.1	72.7	32.8	21.6	84.9	60.8	39.9
8	159.5	68.5	101.0	83.7	93.2	42.1	91.8	63.5	32.5	18.9	75.8	50.5	36.7
9	160.1	70.8	100.6	82.8	93.6	42.8	88.9	61.1	29.9	19.0	75.0	49.1	36.2
10	169.9	74.7	108.4	90.3	100.8	45.3	95.8	68.0	33.8	20.7	80.4	53.2	36.2
11	162.0	72.2	100.5	84.6	93.5	43.3	93.7	66.1	28.3	20.0	80.8	52.3	37.3
12	160.1	70.5	99.2	82.1	93.4	42.2	89.3	62.0	28.8	19.1	71.6	50.8	36.9
13	173.2	80.7	110.4	91.7	103.4	47.8	92.6	65.5	29.7	18.6	79.8	53.0	35.7
14	169.9	75.4	106.1	87.6	98.2	47.0	95.5	68.7	30.7	20.7	80.8	57.2	37.6
15	166.6	72.0	105.7	87.5	99.9	45.7	96.5	69.9	33.8	19.5	83.4	54.8	38.4
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
106	156.1	68.9	95.8	79.8	89.1	41.4	85.6	69.0	26.9	19.5	75.1	50.3	36.0

Note: h is human body stature; LL_h is human body leg length; WH_h is human body waist height; HH_h is human body hip height; AH_h is human body abdomen height; KH_h is human body knee height; H_h is human body hip circumference; W_h is human body waist circumference; CD_h is human body crotch depth; CW_h is human body crotch width; A_h is human body abdomen circumference; T_h is human body Tight circumference; K_h is human body knee circumference. Please see Appendix 1 about the detailed anthropometric data.

Actually, data acquired from instrumental and human experiments are generally incomplete, then it is inappropriate to process raw data directly without any preprocessing [133]. In our study, the test of outliers is applied for preprocessing the anthropometric data. By using the method of 3σ-rule [133], I detect some outliers and validate most of the acquired data. As the special body data, corresponding to outliers, usually lead to wrong analysis results, I exclude them, which account for about 8% of total sample size only. The remaining data are eligible and will be used in the following procedures of data analysis (Table 3-1).

(3) Factor analysis

Table 3-2 KMO and Bartlett test

KMO	Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	0.791
Bartlett's Test of Sphericity	Approx. Chi-Square	2290.396
	df	78.000
	$Sig.$	0.000

Note: df stands for degrees of freedom; $Sig.$ stands for minimum significance.

Table 3-3 Rotated component matrix of anthropometric measurement

NO.	Measuring items	Abbr.	Component	
			1	2
1	Height	h	0.960	0.205
2	Human body Waist Height	WH_h	0.956	0.193
3	Human body Abdomen Height	AH_h	0.930	0.152
4	Human body Hip Height	HH_h	0.941	0.166
5	Human body Leg Length	LL_h	0.894	0.006
6	Human body Knee Height	KH_h	0.903	0.228
7	Human body Waist girth	W_h	0.002	0.915
8	Human body Abdomen girth	A_h	0.202	0.919
9	Human body Hip girth	H_h	0.279	0.902
10	Human body Thigh girth	T_h	0.178	0.916
11	Human body Knee girth	K_h	0.227	0.775
12	Human body Crotch Width	CW_h	0.040	0.854

Note: Extraction method is principal component analysis; Rotation method is varimax with Kaiser Normalization. As crotch depth CD_h equals waist height WH_h minus leg length LL_h(see Figure 3-3), it does not involve factor analysis.

After the data preprocessing, I utilize factor analysis, which is widely applied for data reduction or structure detection, to process the eligible data. The aims of factor analysis are: (1) reducing the number of anthropometric items and (2) detecting the significant classes among all the anthropometric items. Kaiser-Meyer-Olkin (KMO) [134-136] and Bartlett test

[135] are first applied to test whether factor analysis is appropriate or not to the data. In Table 3-2, the KMO value is about 0.8, indicating that, factor analysis can be meritoriously conducted [137]; the significance ($sig.$) value is 0, indicating that the hypothesis of independence is rejected, thereby providing evidence that factor analysis is really suitable to the data [135].

According to the factor loading coefficients of the rotated component matrix shown in Table 3-3, I extract the first two components. The accumulative contribution of the first two factors accounts for 85.86% (Table 3-4) of variability. It indicates that the two factors can represent the main information on human body dimensions in this target population. The first factor mainly includes stature, inside length, waist height, hip height, abdomen height and knee height. These measuring items reflect the different height dimensions on the human body. Therefore, I denote all of them as "height factor" [21]. The second factor mainly includes crotch width, waist, abdomen, thigh, and knee. These measuring items reflect the thickness and circumferences of different parts on the lower body. As the width has a strong correlation with the circumference, I denote all of them as "girth factor" [21].

Table 3-4 Total variance explained

Component	Factor	Initial Eigenvalues		
		Total	% of Variance	Cumulative %
1	Height factor	6.29	48.40	48.40
2	Girth factor	4.87	37.47	85.86

Note: Extraction method is principal component analysis.

(4) Correlation analysis

Using factor analysis, I find that two factors can influence human body dimensions significantly and each factor contains several measuring items. In order to reduce the number of redundant measures, correlation analysis is applied to find the key measuring items for these two factors. As shown in Table 3-5, all the measuring items of the height and girth factors have obvious correlations. As the stature is the easiest to be measured, I take it as a key measuring item and can be used for representing the other body dimensions in the height direction. Also, as the waist and hip girth are easily measured and really important for garment design of the lower body, they are selected as the other two parameters. The other dimensions in girth and width directions can be represented by them. Finally, as result of the above factor analysis and correlation analysis, the dimensions of stature, hip and waist are selected as three dimensional constraint parameters, used for the further analysis.

Table 3-5 Pearson correlation coefficients between 13 measuring items.

	h	WH_h	AH_h	HH_h	LL_h	KH_h	W_h	A_h	H_h	T_h	K_h	CW_h
h	1.00	-	-	-	-	-	-	-	-	-	-	-
WH_h	0.95	1.00	-	-	-	-	-	-	-	-	-	-
AH_h	0.89	0.95	1.00	-	-	-	-	-	-	-	-	-
HH_h	0.92	0.94	0.91	1.00	-	-	-	-	-	-	-	-
LL_h	0.85	0.81	0.78	0.81	1.00	-	-	-	-	-	-	-
KH_h	0.92	0.88	0.83	0.85	0.81	1.00	-	-	-	-	-	-
W_h	0.19	0.19	0.14	0.14	0.07	0.21	1.00	-	-	-	-	-
A_h	0.39	0.37	0.33	0.32	0.20	0.39	0.88	1.00	-	-	-	-
H_h	0.47	0.45	0.41	0.41	0.20	0.44	0.75	0.88	1.00	-	-	-
T_h	0.36	0.34	0.29	0.33	0.15	0.37	0.78	0.84	0.90	1.00	-	-
K_h	0.36	0.36	0.34	0.32	0.18	0.40	0.65	0.70	0.71	0.74	1.00	-
CW_h	0.20	0.19	0.17	0.21	0.09	0.22	0.76	0.73	0.77	0.74	0.56	1.00

Note: h is human body stature; WH_h is human body Waist Height; AH_h is human body Abdomen Height; HH_h is human body Hip Height; LL_h is human body Leg Length; KH_h is human body Knee Height; W_h is human body Waist girth; A_h is human body Abdomen girth; H_h is human body Hip girth; T_h is human body Thigh girth; K_h is human body Knee girth; and CW_h is human body Crotch Width.

(5) Linear regression analysis

Table 3-6 Linear regression analysis and modeling

No.	Model	R^2	Adjusted R^2	F	$Sig.$
1	$WH_h = 0.745h - 19.344$	0.90	0.90	942.44	0.00
2	$HH_h = 0.686h - 28.210$	0.85	0.85	1402.51	0.00
3	$CD_h = 0.532h - 14.478$	0.72	0.72	276.16	0.00
4	$KH_h = 0.367h - 15.911$	0.85	0.84	579.89	0.00

Note: h is human body stature; WH_h is human body waist height; HH_h is human body hip height; CD_h is human body crotch depth and $CD_h = WH_h - LL_h$; KH_h is human body knee height; $Sig.$ is significance; Confidence level is 95%; R^2 is R square.

Next, linear regression is used for modeling the dependent relations of the other body dimensions in the height direction with the unique key dimension (h: stature). As shown in Table 3-6, R-square and adjusted R-square of the proposed models, obtained from linear regression, are both larger than 0.7. This indicates that the fitting level of the linear models is rather high [138-139]. The probabilities of the significance test ($Sig.$) of the four regression formulas are all 0. These results show that there is effectively a significant linear relationship between stature and other dimensions in the height direction [138-139].

3.3.2 Jean flat and pattern associated design in the height direction

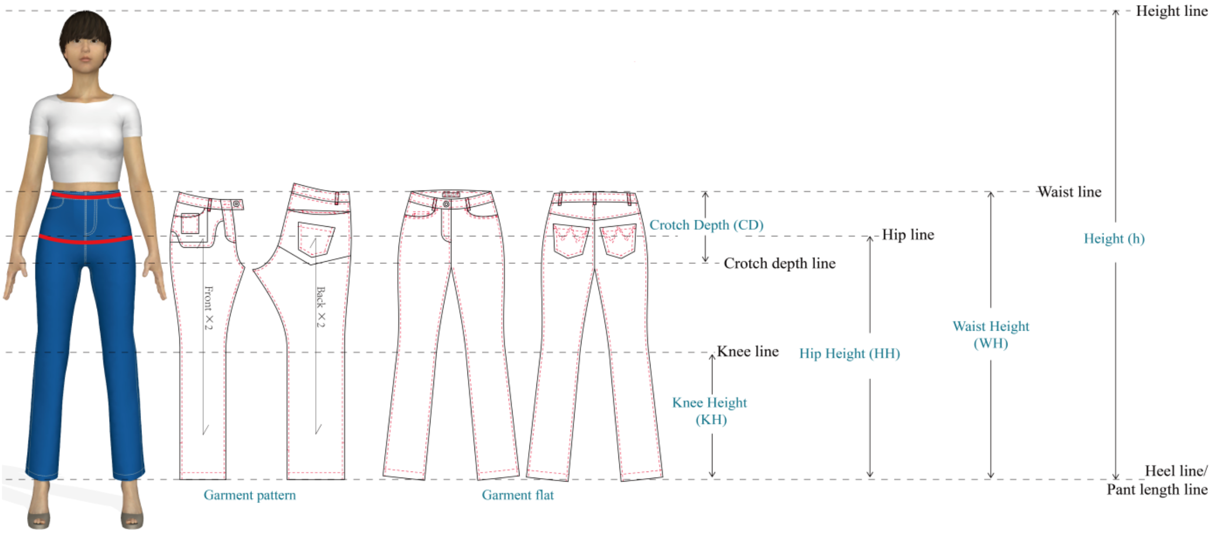


Figure 3-4 Relations between the basic jean flats, basic jean patterns and human body in the height direction.

Firstly, I define a basic jean, whose waistline is corresponding to human body waistline, whose jean length line is corresponding to human body heel line, and whose silhouette is straight. As shown in Figure 3-4, waist height, hip height, crotch depth and knee height are the four useful dimensions needed by jean flat drawing and pattern making in the height direction. According to the previous factor analysis and correlation analysis of anthropometric data, I take height as the key dimension (parameter) to represent all the four useful dimensions in the height direction required by jean flat drawing and pattern making. As linear models are widely applied in pattern making [16, 2], the functions $f_i(\cdot)(i = 1, \ldots, n)$ in Formulas (3-7) and (3-8) are considered as linear models obtained by linear regression. The four useful dimensions in the height direction for jeans can be calculated according to the linear models shown in Table 3-5, i.e.

$$WH_f = WH_p = 0.745h - 19.344 \tag{3-12}$$

$$HH_f = HH_p = 0.686h - 28.210 \tag{3-13}$$

$$CD_f = CD_p = 0.532h - 14.478 \tag{3-14}$$

$$KH_f = KH_p = 0.367h - 15.911 \tag{3-15}$$

where h is human body stature; WH_f, HH_f, CD_f and KH_f are waist height, hip height, crotch depth and knee height of the basic jean flat; WH_p, HH_p, CD_p and KH_p are waist height, hip height, crotch depth and knee height of the basic jean pattern.

3.3.3 Jean flat and pattern associated design in the width direction

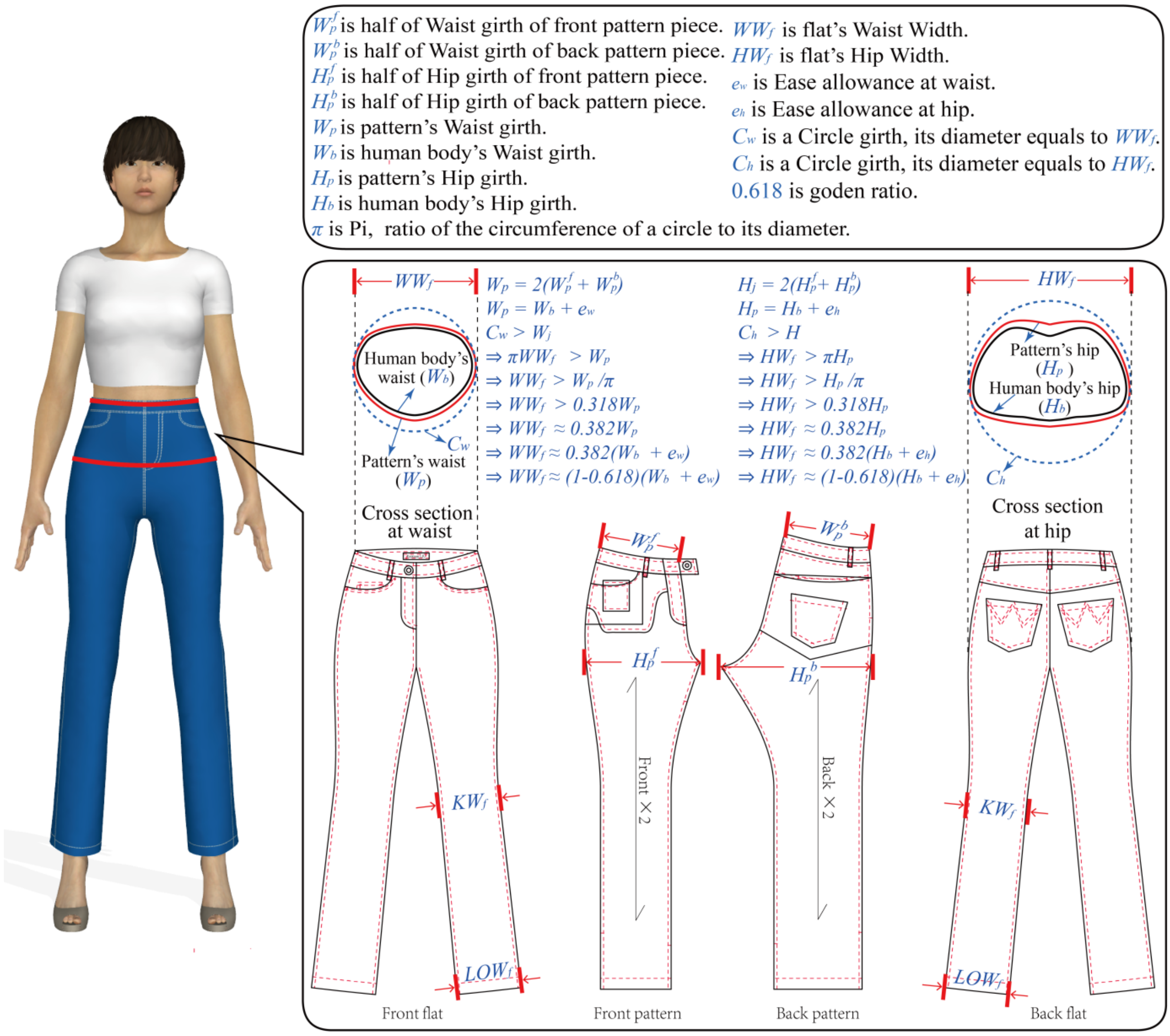


Figure 3-5 Relations between the basic jean flats, patterns and human body in the width direction.

As shown in Figure 3-5, waist width, hip width, knee width and leg opening width are the four useful dimensions needed for drawing a jean flat drawing, while waist girth, hip girth, knee girth and leg opening girth are the four useful dimensions needed for pattern making. Factor analysis and correlation analysis of anthropometric data show that hip girth and waist girth can represent all the dimensions in the width direction [21]. Therefore, I take them as the key body dimensions in the width direction to represent all the four useful dimensions in this direction for jean pattern making. As Formulas (3-7) and (3-9) show that the flat dimensions have relations with the corresponding human body dimensions, I also take hip girth and waist girth as the key body dimensions in the width direction to represent the four useful dimensions needed for flat drawing. As linear models are widely applied in pattern making

[16, 2], the functions $g_j(\cdot)$ in Formulas (3-9) and (3-10) are set to be linear models. According to Formulas (3-9) and (3-10), the eight useful dimensions in the width direction are represented by hip girth and waist girth respectively, as follows:

$$W_p = W_b + e_w \tag{3-16}$$

$$H_p = H_b + e_h \tag{3-17}$$

$$K_p = 0.4H_b + c_k \tag{3-18}$$

$$LO_p = 0.4H_b + c_{lo} \tag{3-19}$$

$$WW_f = (1 - 0.618)(W_b + e_w) \tag{3-20}$$

$$HW_f = (1 - 0.618)(H_b + e_h) \tag{3-21}$$

$$KW_f = (1 - 0.618)(0.4H_b + c_k) \tag{3-22}$$

$$LOW_f = (1 - 0.618)(0.4H_b + c_{lo}) \tag{3-23}$$

where W_p, H_p, $K_p$and LO_b are the basic jean pattern's waist girth, hip girth, knee girth and leg opening girth respectively; WW_f, HW_f $KW_f$and LOW_f are the basic jean flat's waist width, hip width, knee width and leg opening width respectively; H_b and W_b are human body' waist girth and hip; e_w and e_h are jeans' ease allowances at waist and hip respectively; c_k and c_{lo} are constants, their values depend on jean styles respectively.

It is noticed that Formulas (3-18) and (3-19) are obtained from the Zhang's work [16]. Formulas (3-20), (3-21), (3-22) and (3-23) are deduced based on Formulas (3-9), (3-18) and (3-19). Figure 3-5 shows a detailed derivation process of WW_f and HW_f again (I have already deduced in Formula (3-2)), while KW_f and LOW_f are deduced using the same method.

All the dimensions of jeans related to pattern making in the width direction, such as knee girth, leg opening girth, pocket width, are derived from Formula (3-16), (3-17), (3-18) and (3-19). Meanwhile, all the dimensions of jeans related to flat drawing in the width direction, such as knee width, leg opening width, and pocket width, are derived from Formulas (3-20), (3-21), (3-22) and (3-23).

3.3.4 Jean style design

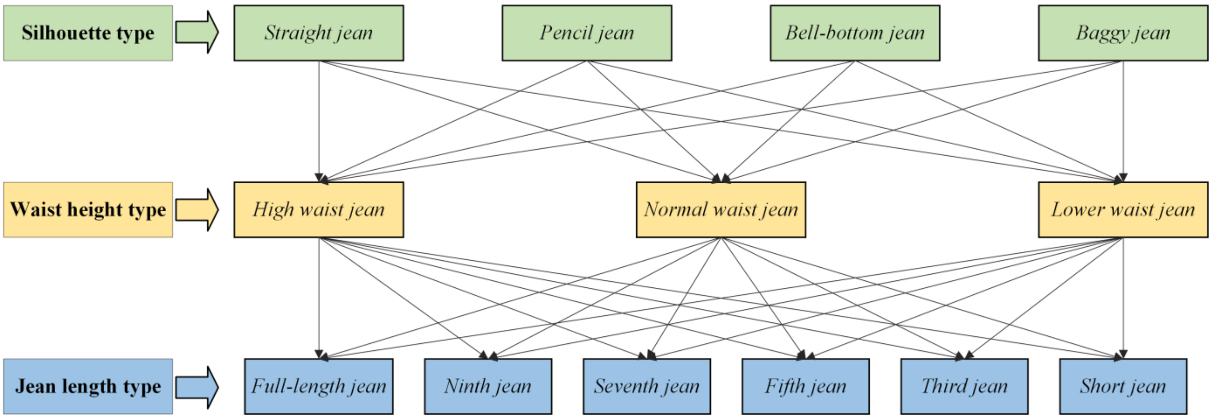


Figure 3-6 Jean style classification.

It has been founded that a garment shape depends on two types of constraint parameters: dimensional constraint parameters and geometric constraint parameters [39]. In Sections 3.3.1 and 3.3.2, I have established the relations between dimensional constraint parameters and jean flat dimensions. Now I will establish the relations between geometric constraint parameters and jean flat dimensions. I conducted a questionnaire survey of 20 designers. From the questionnaire result in Figure 3-6, I learn that the silhouettes of jeans are usually classified into four categories: pencil jean, straight jean, bell-bottom jean and baggy jean.

(1) Silhouette design

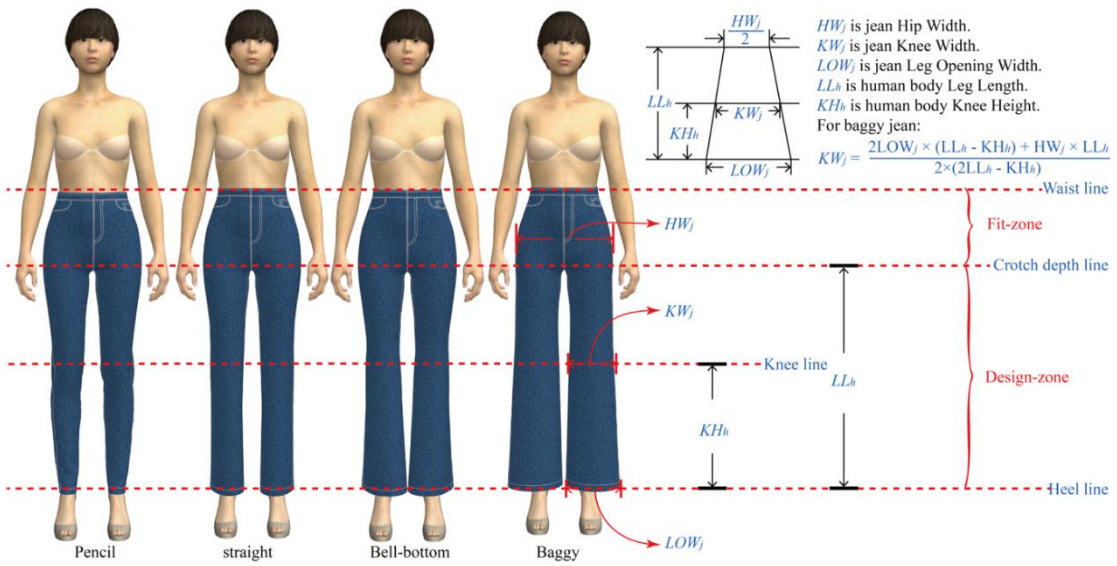


Figure 3-7 Jean silhouette design.

As shown in Figure 3-7, the zone between waistline and crotch depth line is the fit zone; and that below the crotch depth line is the design zone. Jeans should fit well in the fit-zone. Meanwhile, designers can design various jeans in this zone. Thus, jean styles' characteristics mainly depend on the part below crotch depth line. Further, I found that the main differences in jean silhouettes are values of the knee width and leg opening width (Figure 3-7). Especially, the main difference in pencil jean, straight jean and bell-bottom jean are the values of leg opening girth. Based on the above analysis, I define jean silhouette as follows:

$$Silhouette = \begin{cases} "V", \quad (LOW_j = KW_j - \alpha) \\ "H", \quad (LOW_j = KW_j) \\ "X", \quad (LOW_j = KW_j + \beta) \\ "A", \quad \begin{pmatrix} LOW_j = \dfrac{HW_j}{2} + \gamma \\ KW_j = \dfrac{2LOW_j \times (LL_h - KH_h) + HW_j \times LL_h}{2(2LL_h - KH_h)} \end{pmatrix} \end{cases} \tag{3-24}$$

where "V", "H", "X" and "A" are pencil jean, straight jean, bell-bottom jean and baggy jean respectively; LOW_{j} is jean Leg Opening Width; KW_{j} is jean Knee Width; HW_{j} is jean Hip Width; KH_h is human body Knee Height; LL_h is human body Leg length; α, β and γ are positive constants, and their values depend on design requirements.

It is noticed that the baggy jean is different from other three silhouette types. Leg opening width's values of pencil jean, straight jean and bell-bottom jean depend on their knee width. Conversely, knee width's value of baggy jeans depends on their leg opening width. For baggy jeans, I consider the design zone of baggy jeans as a trapezoid; the trapezoid's topline width is half of jean hip width ($HW_{\mathrm{j}}/2$); the trapezoid's baseline width is jean leg opening width ($HW_{\mathrm{j}}/2 + \gamma$); the value of jean knee width can be calculated according to the area formula (Figure 3-7). Formula (3-24) is useful for a parametric design of jean silhouette.

(2) Waist design

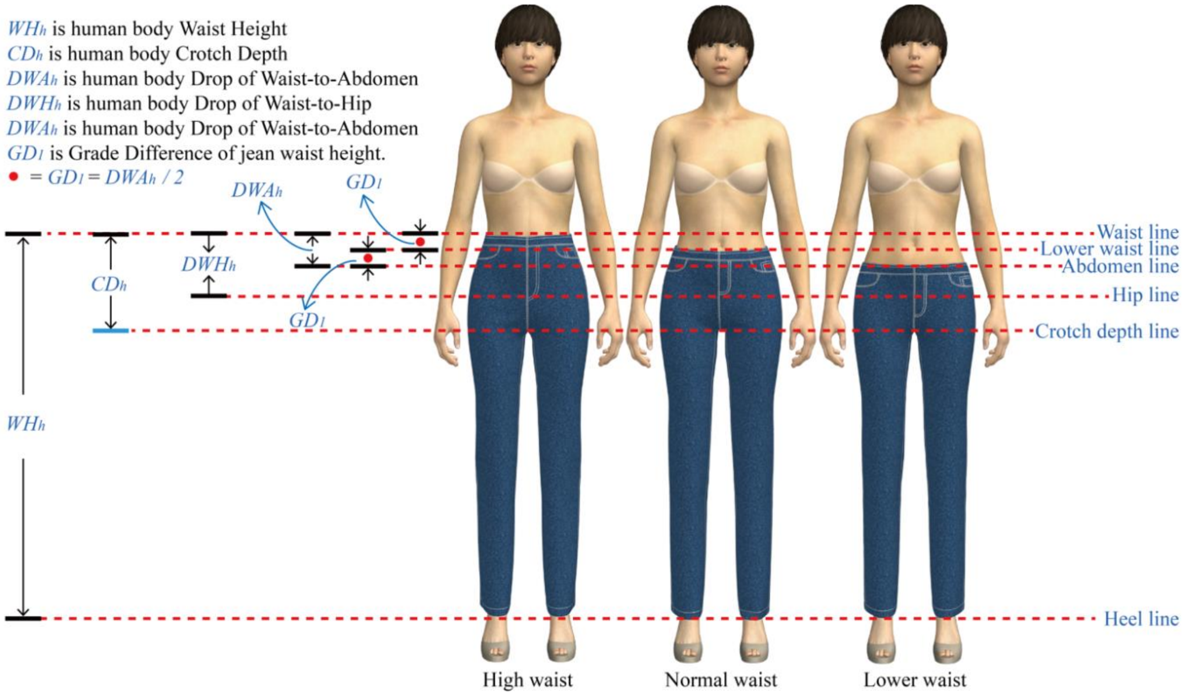


Figure 3-8 Jean waist design.

From the result of our questionnaire survey in Figure 3-6, I learn that jean waist type is generally classified into three categories: high waist, normal waist and lower waist (Figure 3-6). As shown in Figure 3-8, the high waist jean's waistline corresponds to human body waistline; while the lower waist jean's waistline corresponds to human body abdomen line, and the normal waist jean's waistline is at about the middle of human body waistline and abdomen line. According to the above analysis, the grade difference of a jean waist type is given as follows.

$$GD_1 = DWA_h /2 \tag{3-25}$$

where DWA_h is human body Drop of Waist-to-Abdomen, GD_1 the Grade Difference of jean waist height.

With further analysis, I find that the main differences in waist types are values of the crotch depth and drop of waist-to-hip (Figure 3-8). By combining them with the grade difference of jean waist (Formula (3-25)), I define jean waist parameters as follows:

$$Waist\ type = \begin{cases} Height\ waist, \begin{pmatrix} CD_j = CD_h \\ DWH_j = DWH_h \end{pmatrix} \\ Normal\ waist, \quad \begin{pmatrix} CD_j = CD_h - GD_1 \\ DWH_j = DWH_h - GD_1 \end{pmatrix} \\ Lower\ waist, \begin{pmatrix} CD_j = CD_h - 2GD_1 \\ DWH_j = DWH_h - 2GD_1 \end{pmatrix} \end{cases} \tag{3-26}$$

where GD_1 is the Grade Difference of jean waist height; CD_j is jean Crotch Depth;DWH_j is jean Drop of Waist-to-Hip; CD_h is human body Crotch Depth; DWH_h is human body Drop of Waist-to-Hip. Formula (3-26) was applied to design jean waist type.

(3) Length design

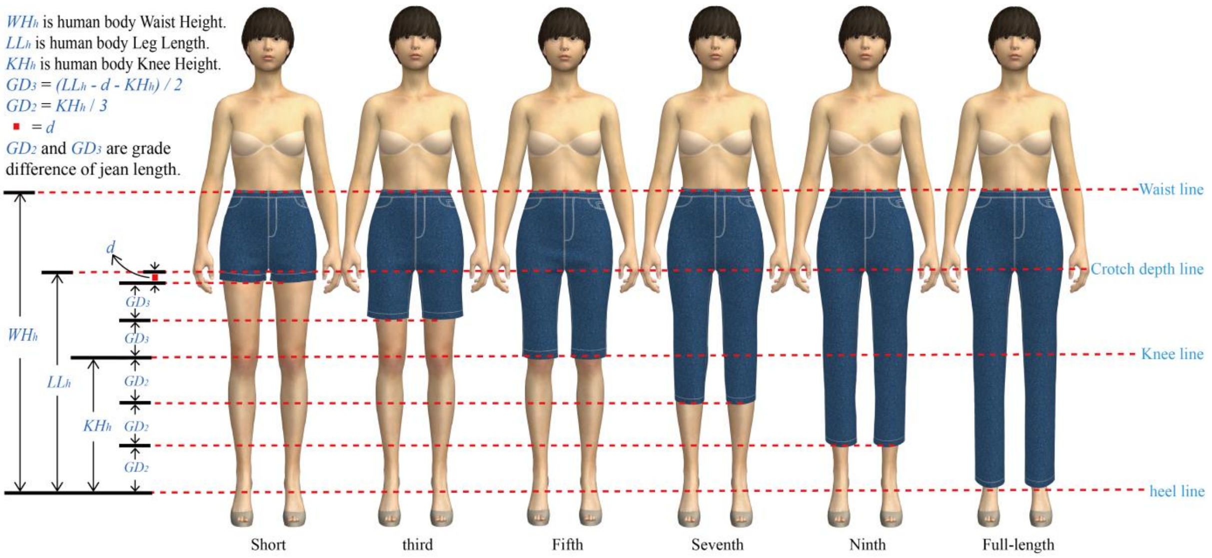


Figure 3-9 Jean length design.

From the previous questionnaire in Figure 3-6, I find that jean lengths can be classified into six categories: short jeans, third-jeans, fifth-jeans, seventh-jeans, ninth-jeans and full-length jeans (Figure 3-6). As shown in Figure 3-9, the short jean's length line is d cm below crotch depth line (The value of d depends on design requirements); the fifth jean's length line corresponds to human body knee line; the full-length jean's length line corresponds to human body leg length line. The third jean's length line is located at the middle of short jean's length line and fifth jean's length line. The locations of the seventh and ninth jeans' length lines enable to uniformly divide the length from knee line to heel line. According to the above analysis, the grade differences of jean lengths are given below.

$$GD_2 = KH_h/3 \tag{3-27}$$

$$GD_3 = (LL_h - d - KH_h)/2 \tag{3-28}$$

where GD_2 is the Grade Difference of a full-length, ninth, seventh, and fifth jeans; GD_3 is the Grade Difference of a short, third and fifth jeans; KH_h is the human body Knee Height; LL_h is the human body Leg Length; d is a positive constant, whose value depends on design requirements.

Further, I also find that the main differences of jean length styles are related to waist height and drop of waist-to-abdomen, knee height and length (Fig. 6). By combining the grade differences of jean lengths GD_1, GD_2, GD_3 in Formulas (3-25), (3-27) and (3-28), I quantitatively deduce the different length styles as follows:

$$Jean\ length = \begin{cases} full-length, \begin{pmatrix} JL = WH_h, height\ waist \\ JL = WH_h - GD_1, normal\ waist \\ JL = WH_h - 2GD_1, lower\ waist \end{pmatrix} \\ ninth, \begin{pmatrix} JL = WH_h - GD_2, height\ waist \\ JL = WH_h - GD_2 - GD_1, normal\ waist \\ JL = WH_h - GD_2 - 2GD_1, lower\ waist \end{pmatrix} \\ seventh, \begin{pmatrix} JL = WH_h - 2GD_2, height\ waist \\ JL = WH_h - 2GD_2 - GD_1, normal\ waist \\ JL = WH_h - 2GD_2 - 2GD_1, lower\ waist \end{pmatrix} \\ fifth, \begin{pmatrix} JL = WH_h - 3GD_2, height\ waist \\ JL = WH_h - 3GD_2 - GD_1, normal\ waist \\ JL = WH_h - 3GD_2 - 2GD_1, lower\ waist \end{pmatrix} \\ third, \begin{pmatrix} JL = WH_h - 3GD_2 - GD_3, height\ waist \\ JL = WH_h - 3GD_2 - GD_3 - GD_1, normal\ waist \\ JL = WH_h - 3GD_2 - GD_3 - 2GD_1, lower\ waist \end{pmatrix} \\ short, \begin{pmatrix} JL = WH_h - 3GD_2 - 2GD_3, height\ waist \\ JL = WH_h - 3GD_2 - 2GD_3 - GD_1, normal\ waist \\ JL = WH_h - 3GD_2 - 2GD_3 - 2GD_1, lower\ waist \end{pmatrix} \end{cases} \quad (3\text{-}29)$$

where JL is the Jean Length; WH_{h} is the human body Waist Height; GD_1 is the Grade Difference of jean waist height; GD_2 is the Grade Difference of full-length, ninth, seventh, and fifth jeans; GD_3 is the Grade Difference of short, third and fifth jeans. Formula (3-29) can be applied to design jean length styles.

3.3.5 Jean flat and pattern auto-generation system

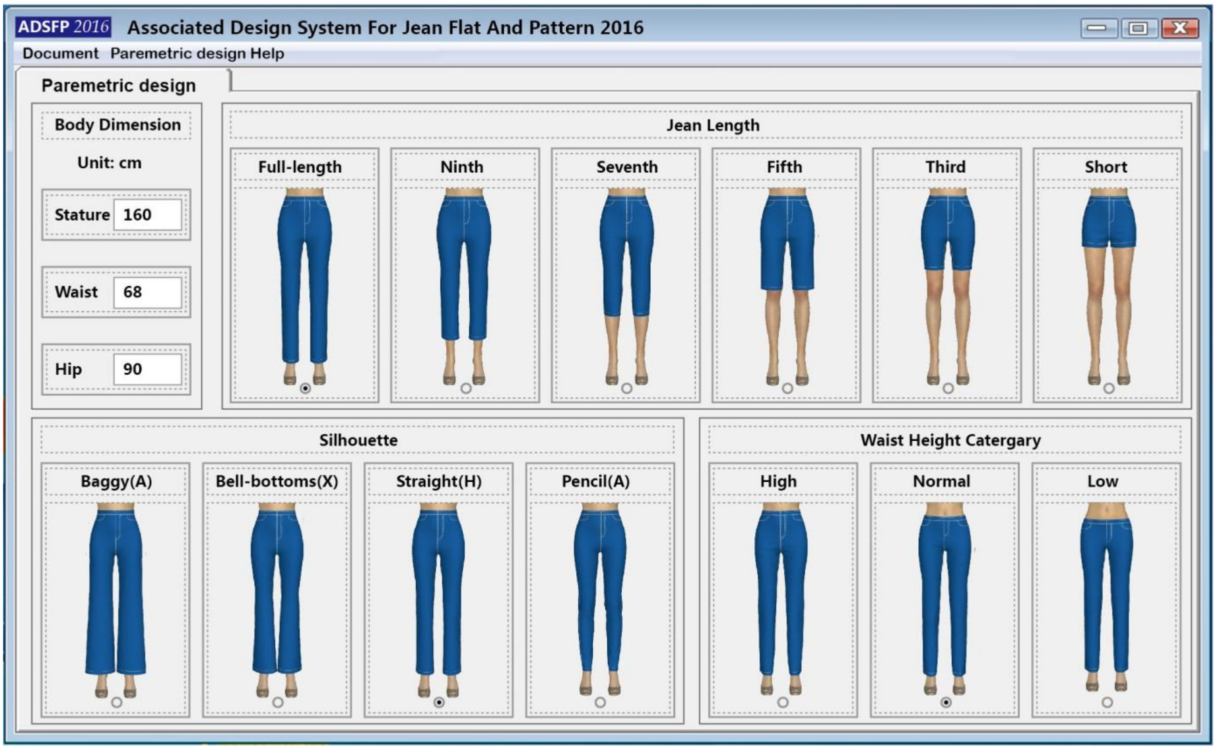


Figure 3-10 Interactive interfaces of associated design system for jean flat and pattern 2016.

By integrating the previous technology (models and data), I develop a software system called Associate Design System for jean Flats and Patterns (ADSFP2016) in order to generate jean flats and patterns automatically and simultaneously. In this system, all the dimensions of garment flats and patterns in height and width directions are calculated using Formulas (3-12), (3-13), (3-14), (3-15), (3-16), (3-17), (3-18), (3-19), (3-20), (3-21), (3-22) and (3-23). Likewise, all the dimensions of different styles of garment flats and patterns are calculated using Formulas (3-24), (3-25), (3-26), (3-27), (3-28) and (3-29). As shown in Figure 3-10, for a specific customer, ADSFP2016 has six input parameters: jean length, silhouette, waist height category, human body stature, human body waist girth and human body hip girth. Meanwhile, the outputs of this system are jean flats and their associated patterns.

In a design process, a fashion designer usually needs several hours for drawing a complex garment flat. Similarly, a pattern maker needs several days for transforming a complex flat into its associated pattern. With the help of ADSFP2016, different jean flats and their associated patterns can be generated in a few seconds after input of the corresponding body dimensions and desired style parameters. As shown in Figure 3-11, a series of jean flats and their associated patterns are generated by adjusting different style parameters in ADSFP2016. By selecting the same style parameters, the generated flats and patterns can easily vary with body dimensions. Therefore, the proposed system can help designers to generate individual jean flats and patterns with different sizes and styles within a very short time. The generated flats, taking into account personalized customers' body dimensions, will be very useful for made-to-measure and mass customization.

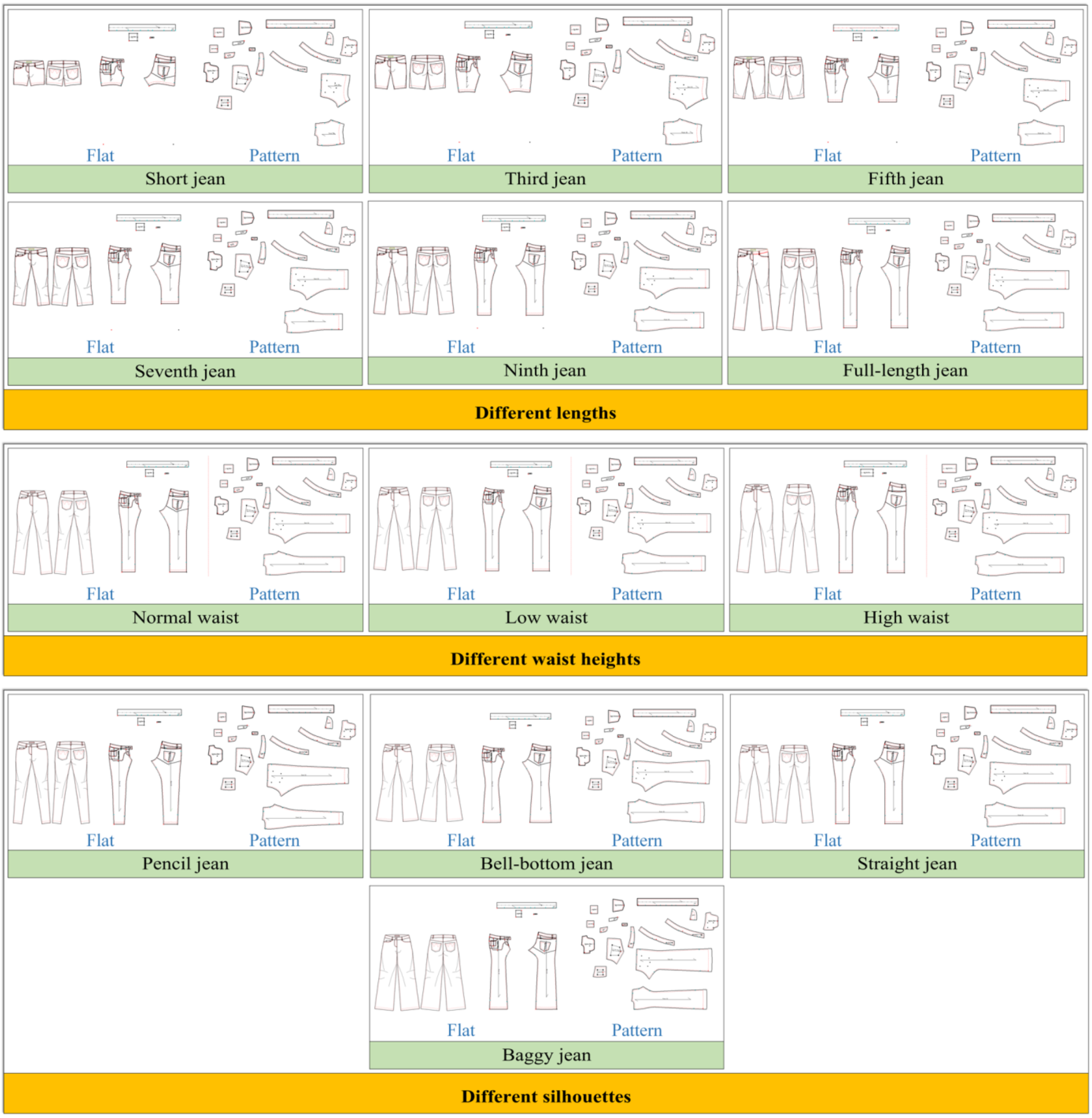


Figure 3-11 Example of flats and patterns of different styles generated by ADSFP 2016.

3.3.6 Validation

Table 3-7 Designer satisfaction survey on jean flats generated by ADSFP2016

Number of evaluators	satisfaction	satisfaction after slight modification	dissatisfaction
20	10	8	2
__	50%	40%	10%

Figure 3-12 Flats and their corresponding patterns and garments.

The key issue of this validation is to test whether the garments made by the generated patterns match up with the corresponding flats. Two experiments have been carried out to evaluate whether jean flats generated by ADSFP2016 meet designers' requirements and accurately reflect their actual garments. In the first experiments, I invite 20 fashion designers coming from a Chinese fashion company to use ADSFP2016. Each designer uses

ADSFP2016 for generating a jean flat according to his/her own idea. After this step, each designer evaluates whether the generated flat fits with his idea or not. The results of designers' satisfaction are showed in Table 3-7, in which 50% of designers directly accept the jean flats generated by the proposed system; 40% of designers accept the jean flats generated by the proposed system after slight modification, for example, pocket only needs to be modified. Only 10% of designers are unsatisfied by the jean flats generated by the proposed system. Because the jean styles they expected are too complex, ADSFP2016 cannot generate them. In general, the jean flats generated by the parametric design method can accurately represent jean's characteristics. They can clearly express the fashion designers' expectations. In the second experiment, three fashion designers use ADSFP2016 to generate three different jean flats and their associated patterns. According to the generated patterns, three pairs of jeans are made. Finally, these jeans and their corresponding flats are evaluated by the three fashion designers. The evaluation results show that all the flats express the fashion designers' concepts clearly, and the garments made of the patterns generated by ADSFP2016 match up with the corresponding flats correctly (Figure 3-12).

In the actual design process, if the garment flats and patterns, generated by the proposed method, do not completely meet the expectations or requirements of a customer or designer, adjustments can be done easily. For example, if a designer is satisfied with the whole flat and pattern, except for the yoke, the only part to be modified is the yoke. As a result, the efficiency of this method is also obviously higher than manual drawing, which would imply redrawing a full new one by hand.

3.4 Discussion

Kim and Lee have pointed out that collaborative product design processes of industrial design and engineering design are very important for consumer product companies [140], the artistic design and engineering design as well. Garment flat drawing belongs to artistic design, while garment pattern making is in the frame of engineering design. This implies that the methods of garment flat drawing and pattern making are completely different. Most scholars study the methods of garment flat drawing or pattern making separately. The previous researches, such as parametric pattern making technology [39], and rapid garment flat generation system [7, 141-142, 3], only deal with the promotion of either flat drawing efficiency or pattern making efficiency. They hardly study the integration of garment flat drawing and pattern making in order to promote design efficiency.

Fashion trends are influenced by seasons, color, style, age, etc. Therefore, designers should develop garment products rapidly to meet customer's individual requirements. However, the separation of drawing flats and making patterns usually leads to two main disadvantages: 1) workload increases significantly; 2) pattern makers misunderstand designers' concepts. The capability of rapid product development is one of core competences for fashion companies. Any research performed inside traditional design processes can rarely improve the design efficiency. Therefore, new methodologies should be proposed to change the current design process. As a novel design concept, GFPADT enables to provide a solution for improving fashion design and engineering design. With the help of GFPADT, the work of fashion designers and pattern makers will be effectively integrated together.

3.5 Conclusion

In this research, I propose GFPADT in order to combine garment flat drawing and pattern making together. I originally endow garment flats with human body dimensions. Hence, a garment flat and its associated patterns are associated by means of human body dimensions. By analyzing the relations between a garment flat, its associated garment patterns and the human body, I construct a series of linear models in both height and width directions for characterizing these relations. These models enable to directly transform garment flats to their associated patterns within a very short time. Compared with traditional methods of garment flat drawing and pattern making, GFPADT has three main advantages. 1) Fashion design efficiency can be improved significantly by directly linking with the engineering design. 2) A design concept can be easily detected on a specific body shape by combining GFPADT and 3D virtual garment fitting. 3) The garment flat drawing and pattern making can be realized automatically by a computer with a very few number of human interventions.

In a broader sense, the general principle proposed in GFPADT can be extended in order to integrate artistic design and engineering design in other sectors, such as architecture, automobile industry and cosmetic industry.

CHAPTER 4: 3D INTERACTIVE GARMENT PATTERN MAKING TECHNOLOGY

Garment pattern making is one of the most difficult tasks in fashion design and production. The traditional pattern making is a typical experience-based work. A junior pattern maker needs several years of professional training for mastering the whole working process and related techniques. This situation seriously restricts the development of new garment products. In this chapter, I propose a 3D Interactive Pattern Making Technology (3DIGPMT) for developing garment patterns in a "what you see is what you get" way. The proposed technology can be applied in made-to-measure, mass customization, mass production, etc.

4.1 General scheme

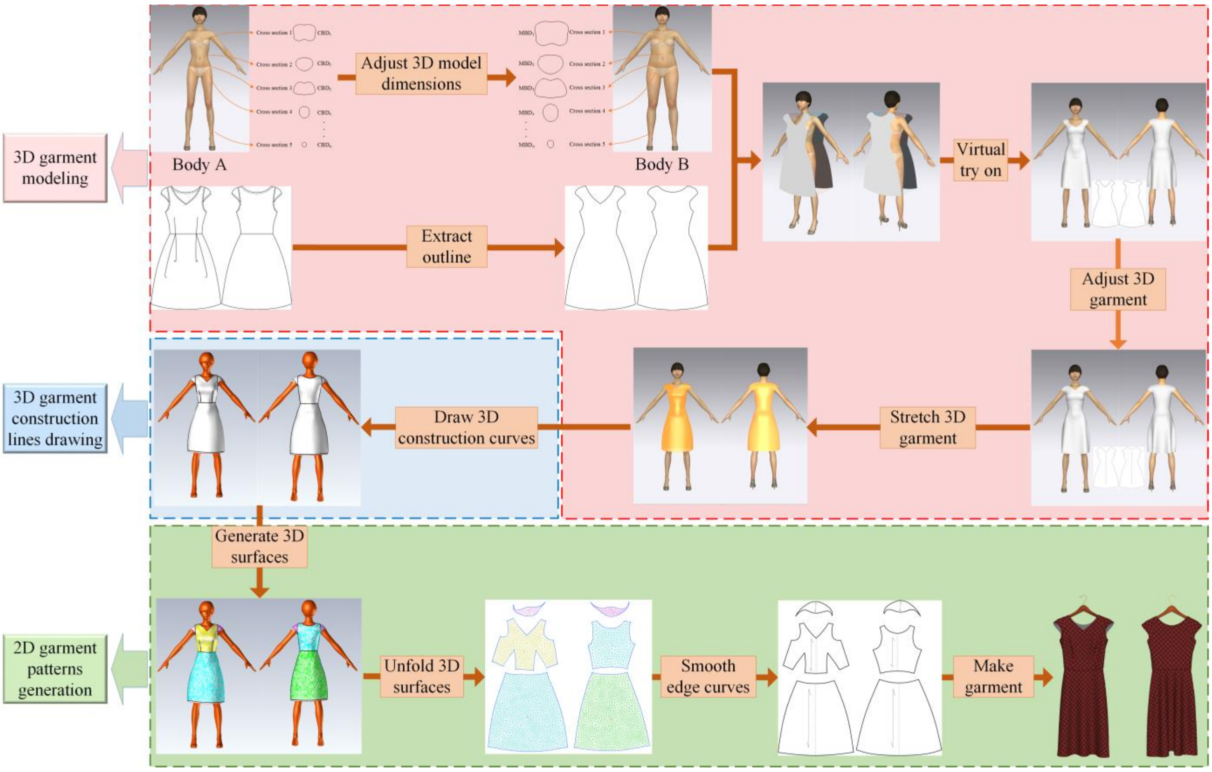


Figure 4-1 General scheme of 3DIGPMT.

The general scheme of 3DIGPMT is described in Figure 4-1. It is made up of three main parts: 3D garment modeling, 3D garment construction lines drawing, and 2D garment patterns generation. The above step realized by CLO 3D and Lectra Designconcept software.

- Frist, I use the front and back outline patterns of a garment flat to make a 3D garment surface on a 3D parametric mannequin, whose dimensions can be adjusted according to the real body dimensions and the required ease allowances.
- Second, I draw a number of garment construction lines on this 3D garment surface. These lines enable to divide the whole surface into many small areas.
- Finally, I flatten these subdivided areas into 2D garment patterns. The 2D garment patterns can be used to make a real garment after a post-processing.

4.2 Methodology

4.2.1 Ease allowance setting

Garment ease allowance is important for both 2D and 3D pattern making. It can be divided into basic ease allowance and style modeling ease allowance. The basic ease allowance refers to the minimal distances between the garment surface and the wearer's body surface at different key positions (hip, waist, bust, etc.), allowing him/her to move freely without uncomfortable feeling. These values need to be set precisely for pattern making. The ease allowance for style modeling is additional distances between the garment surface and the body surface enabling designers to realize the desired style. These values do not need to be set precisely for pattern making.

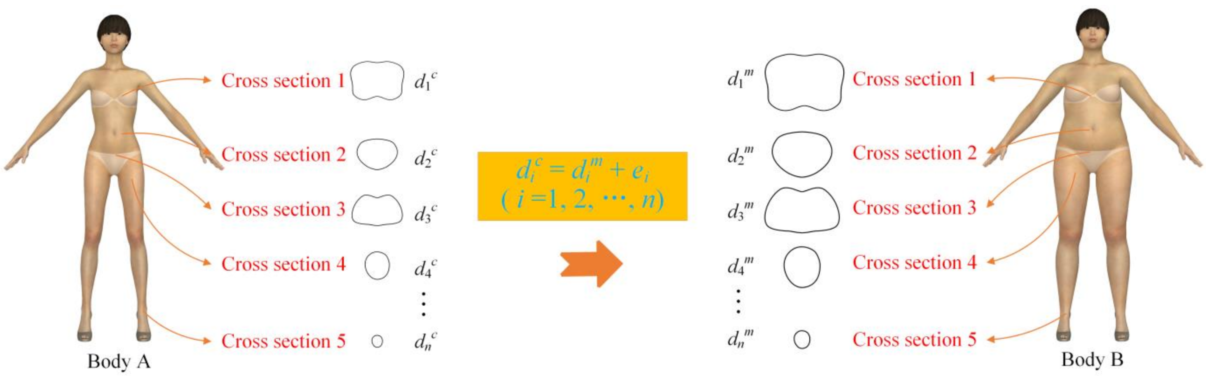


Figure 4-2 Ease allowance setting.

Previous studies on 3D garment pattern making mainly focus on tight garments and rarely consider ease allowance values because it is difficult to accurately set and control these values in a 3D virtual environment due to the complex interactions of materials/human bodies [32-33]. The first step of 3DIGPMT is to set basic ease allowances for a specific customer and style. In this section, I propose a method, deriving from the traditional garment draping method, for accurately setting ease allowance values for 3D pattern making. In the traditional draping process, fashion designers usually append some padding at some special regions in which the ease allowance values are considered as too small. For example, a designer sometimes appends cotton to the position of the mannequin's hip if he/she thinks that the ease allowance is not enough. Using the similar principle, I can directly extend the mannequin's body dimensions by adding the basic easy allowance values to the corresponding positions. As shown in Figure 4-2, Body A is supposed to be a customer and body B an adjustable 3D mannequin. The dimensions of Body A, needed for pattern making, are measured and denoted as d_i^c. The final body dimensions of the mannequin B used for the 3D pattern making are calculated according to the following formula.

$$d_i^m = d_i^c + \mathrm{e}_i^b (i = 1,2, \dots, n) \quad (4\text{-}1)$$

where d_i^m is the body dimension of the adjustable mannequin B at the i-th position; d_i^c is the body dimension of the customer A at the i-th position; e_i^b is the basic ease allowance of the customer at the ith position, whose value depends on the design requirements; n is the number of body positions defined for pattern making.

According to Formula (4-1), I adjust a mannequin's dimensions according to the basic ease allowance values. After that, I design tight garments on the adjusted mannequin whose dimensions are equal to the sums of the customer's body dimensions and the basic ease allowance values. The designed garment is tight for the mannequin, but well adapted to the customer in terms of fit.

4.2.2 3D garment modeling

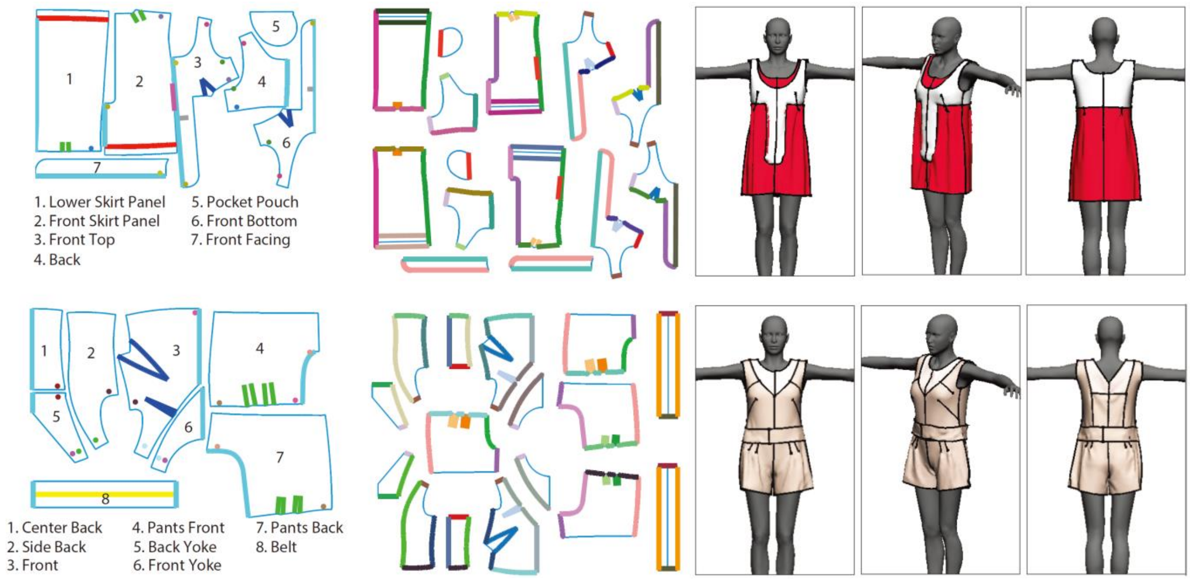


Figure 4-3 Pattern-based garment modeling [143].

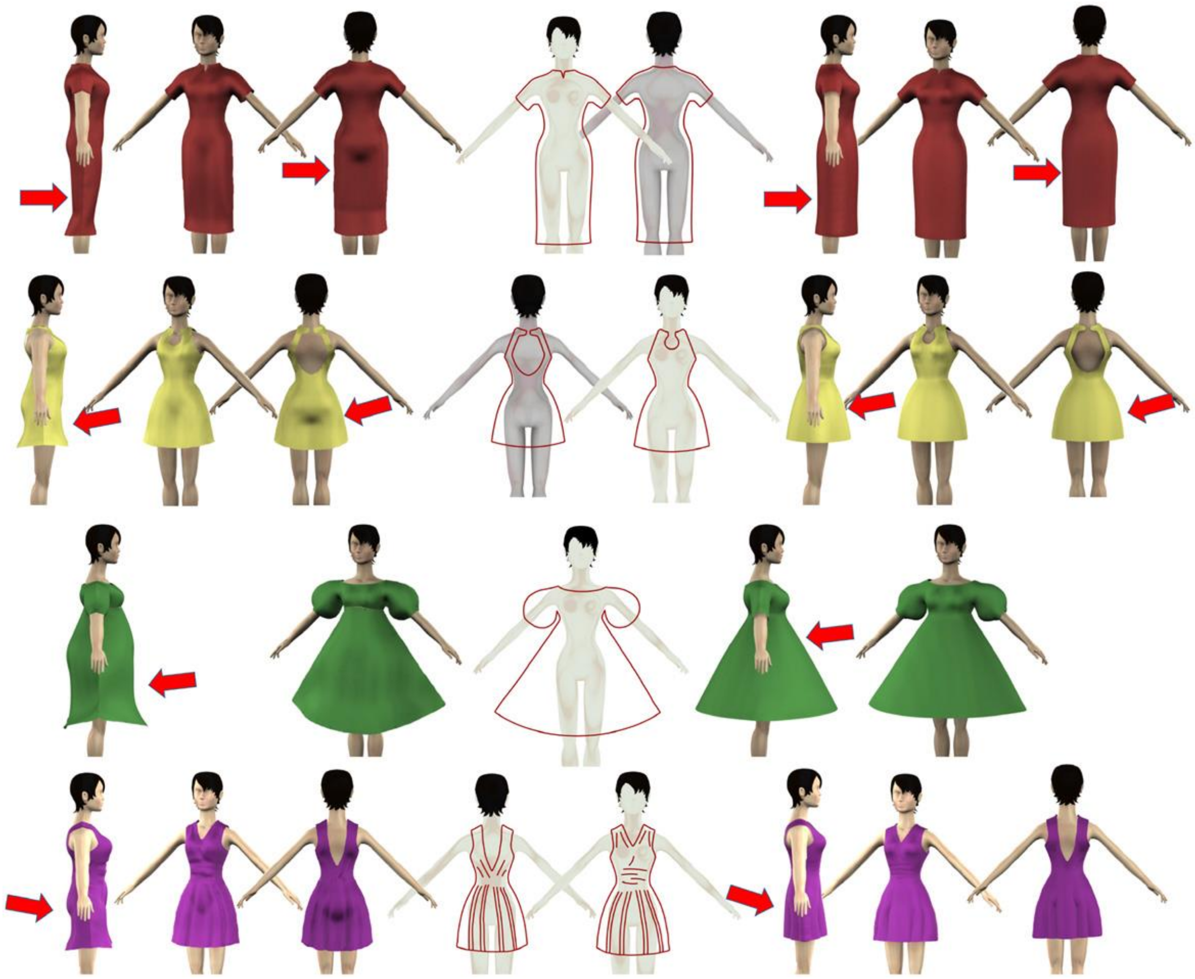


Figure 4-4 Sketch-based garment modeling [11].

Having set ease allowance values, I need to construct the 3D garment surface on the adjusted mannequin. Currently, there are many methods for constructing garment surfaces, such as garment construction using a camera or scanner [144-145], pattern-based garment construction approach [146, 143, 147], 2D sketch-based garment construction approach [148, 9, 11], 3D sketch-based garment construction approach [149-152, 30-33, 153, 54, 43], image-based garment construction approach [154-155], example-based garment construction approach [55], etc. Of these methods, the most popular method is the pattern-based approach. Figure 4-3 shows a typical process of pattern-based garment construction, permitting to simulate the garment-making process using 2D garment patterns by virtual try-on technology. Another efficient approach is the sketch-based method. Figure 4-4 shows a typical process of sketch-based garment construction, in which an operator first draws a 2D garment sketch on a figure, and then a 3D garment surface is generated automatically according to the sketch.

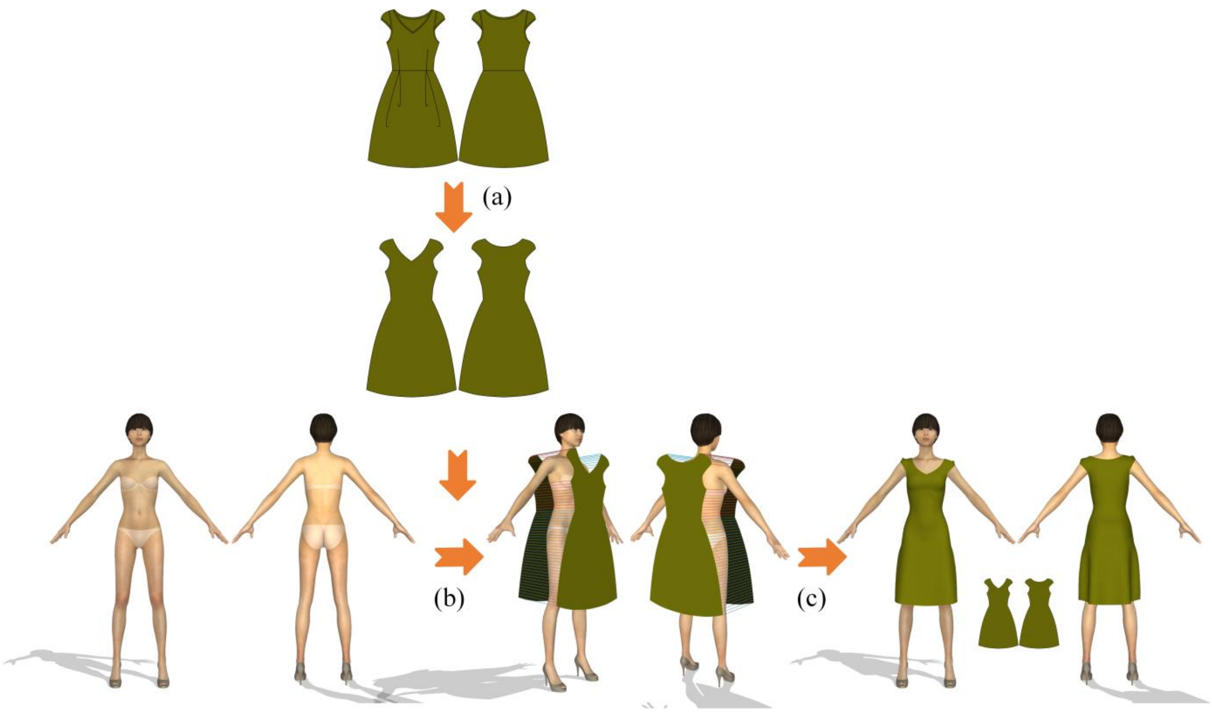


Figure 4-5 3D garment construction using 2D garment outline patterns.

In our study, the main idea on 3D garment construction derives from the pattern-based and sketch-based garment construction approaches. Our aim is to develop garment patterns according to garment flats using human-computer interactive technology. Therefore, I use outlines, which can be easily extracted from garment flats or garment photos, to construct 3D garments. The 3D garment surface constructed by flats' outlines will be similar to the flats. As shown in Figure 4-5(a), I remove the lines from the interior of the flats and keep the outermost contour lines using CAD drawing software like Adobe illustrator, CorelDraw, Lectra Kaledo Style, etc. During outlines drawing, I only focus on the shapes of the flats without considering their precise dimensions. Therefore, mastering the capability of drawing skills is not necessary. Next, I assemble the front and back outline patterns around the mannequin and then sew them together using the virtual try-on technology in order to create a 3D garment surface (Figure 4-5(b) and (c)).

4.2.3 3D garment adjustment

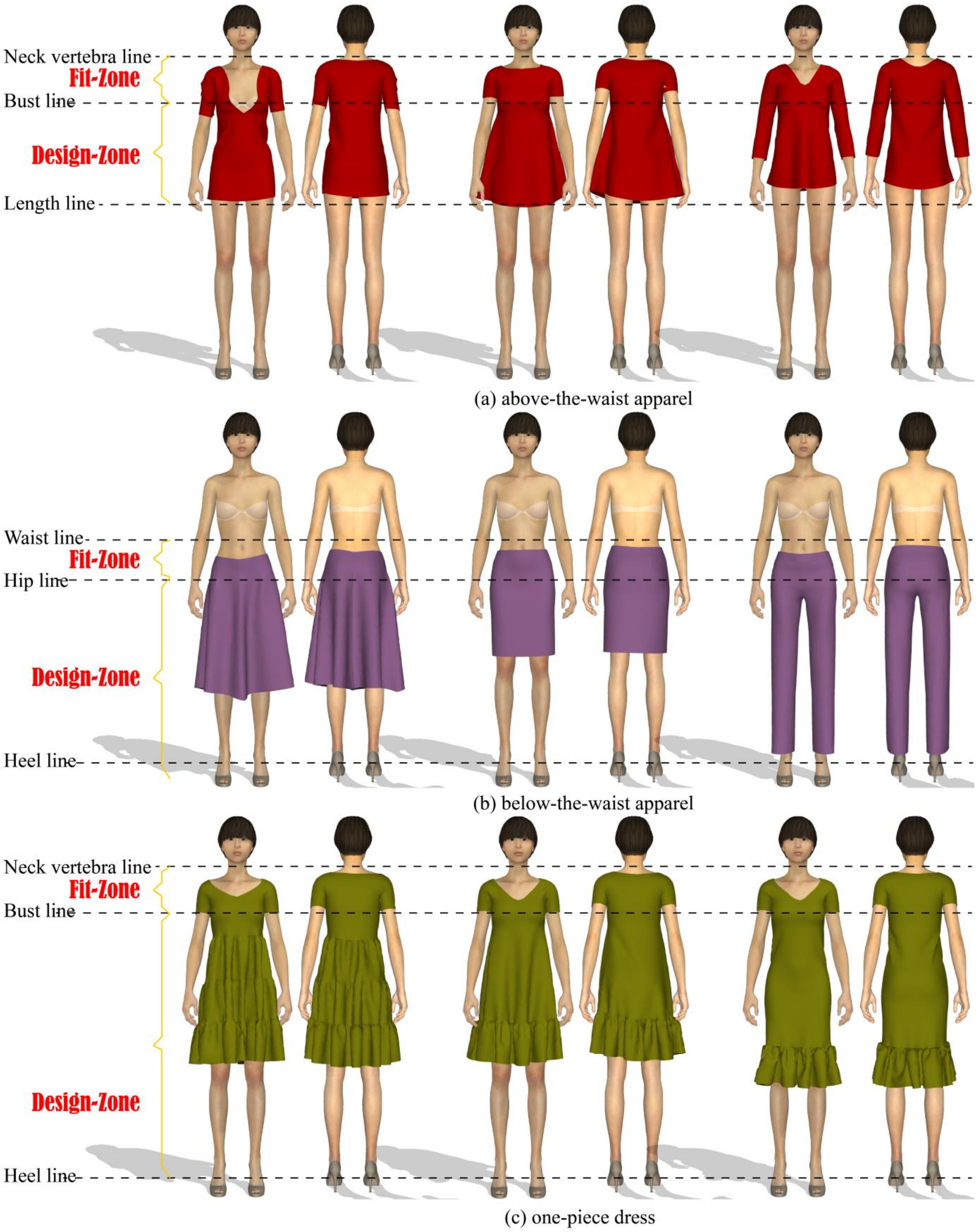


Figure 4-6 Fit zones and design zones of fashion design.

In the above section, I created a 3D garment surface using 2D outline patterns. Nevertheless, such a 3D garment is usually different from the desired style, especially for some details (collar, lengths, pockets, etc.). In this situation, the created 3D garment needs further fine adjustments until it completely meets the desired style.

The adjustment of a 3D garment is related to the fit zones and design zones of the corresponding body surface, defined by fashion designers [21]. Fit zones refer to the crucial areas of the body surface for showing garment fit levels while design zones the crucial areas for showing design ideas and desired garment styles. Garment ease allowance values in the fit zones are mainly related to basic ease allowances, and those in the design zones to style modeling ease allowance values. As shown in Figure 4-6, the fit zones of the above-the-waist garments are located between the neck vertebra line and bust line, and their design zones are located between the bust line and garment length line. The fit zones of the below-the-waist garments are located between the waistline and hip line; and their design zones are located between the hip line and heel line. The fit zones of the one-piece dresses are located between the neck vertebra line and bust line, and their design zones are located between the bust line and heel line.

According to Formula (4-1), I have already added the basic ease allowances to the dimensions of the mannequin. Therefore, the principle of 3D garment adjustment in a fit zone is to ensure the 3D garment surface in tight contact with the mannequin surface in this area. However, the principle of 3D garment adjustment in a design zone is to make the 3D garment surface meet the desired style. By considering the previous principles, I give the formula of 3D garment adjustment as follows:

$$\text{If position } i \in FZ, \text{ then } e_i^m = 0 \; (i = 1,2,\cdots,k) \tag{4-2}$$

$$\text{If position } i \in DZ, \text{ then } e_i^m \geq 0 \; (i = 1,2,\cdots,l) \tag{4-3}$$

where e_i^m is the easy allowance between a 3D garment surface and the mannequin; FZ is the fit zone; DZ is the design zone; k is the total number of positions in the fit zones considered for pattern making; l is the total number of positions in the design zones considered for pattern making.

Having identified the design zone for each style, I will perform a series of operations on the 2D outline patterns in order to recursively adjust the corresponding 3D garment. These operations are based on the principle of Luo et al. [53], who proposed a 3D garment simulation result update algorithm to set up the relationship between 2D garment patterns and its associated 3D garment. By modifying the 2D patterns, its associated 3D garment will be modified automatically and simultaneously. In Section 1.2.3, I have already introduced this method and described its advantages. These advantages include: simplicity, intuition and high efficiency. Any non-professional designer can easily master this technology by directly making interactions between the space of 2D outline patterns adjustment and the space of 3D garment visualization.

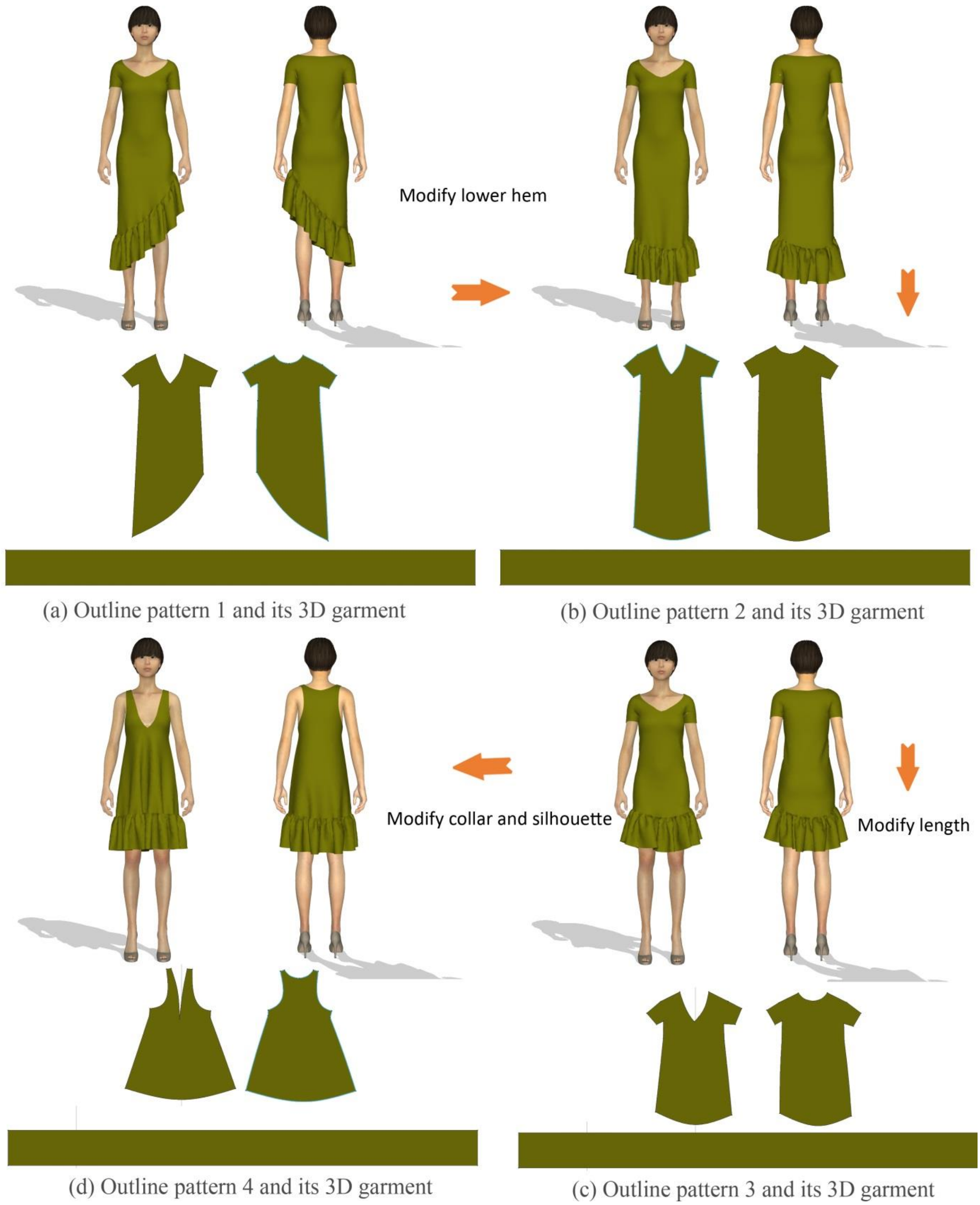


Figure 4-7 3D garment adjustment approach.

As shown in Figure 4-7, by modifying the lower hem, length, collar and silhouette of the patterns respectively, the 3D garment is modified automatically. As 2D outline patterns are not real garment patterns (the 2D outline patterns cannot be used to make clothing), they are only used for 3D garment construction. As shown in Figure 4-8, in the 3D garment adjustment process, I only need to ensure the visual effects of the 3D garment to meet the design requirements and do not care about the shape and dimensions of the outline patterns. The adjustment procedure stops when the shape of the modified 3D garment surface corresponds to the desired design requirements.

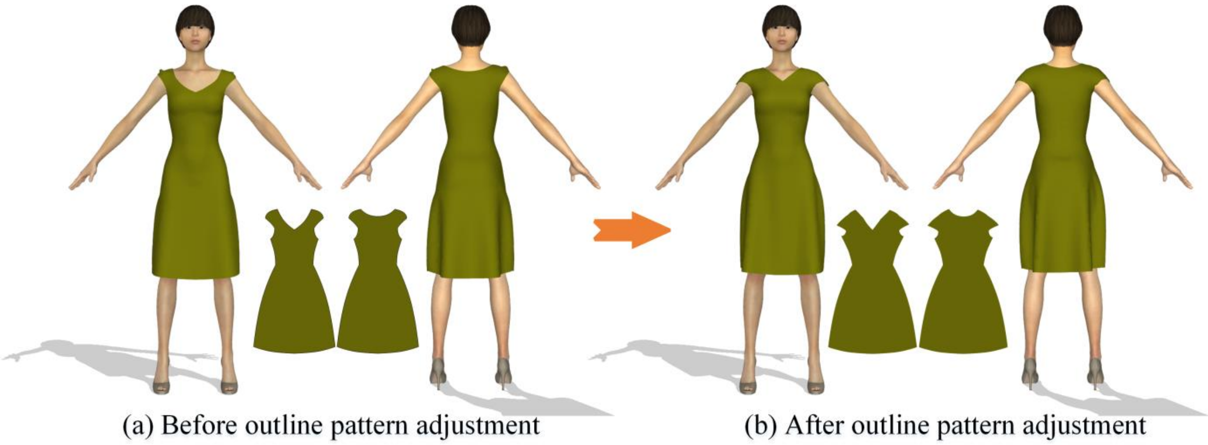


Figure 4-8 3D garment adjustment through 2D outline patterns.

4.2.4 3D garment surface stretching and freezing

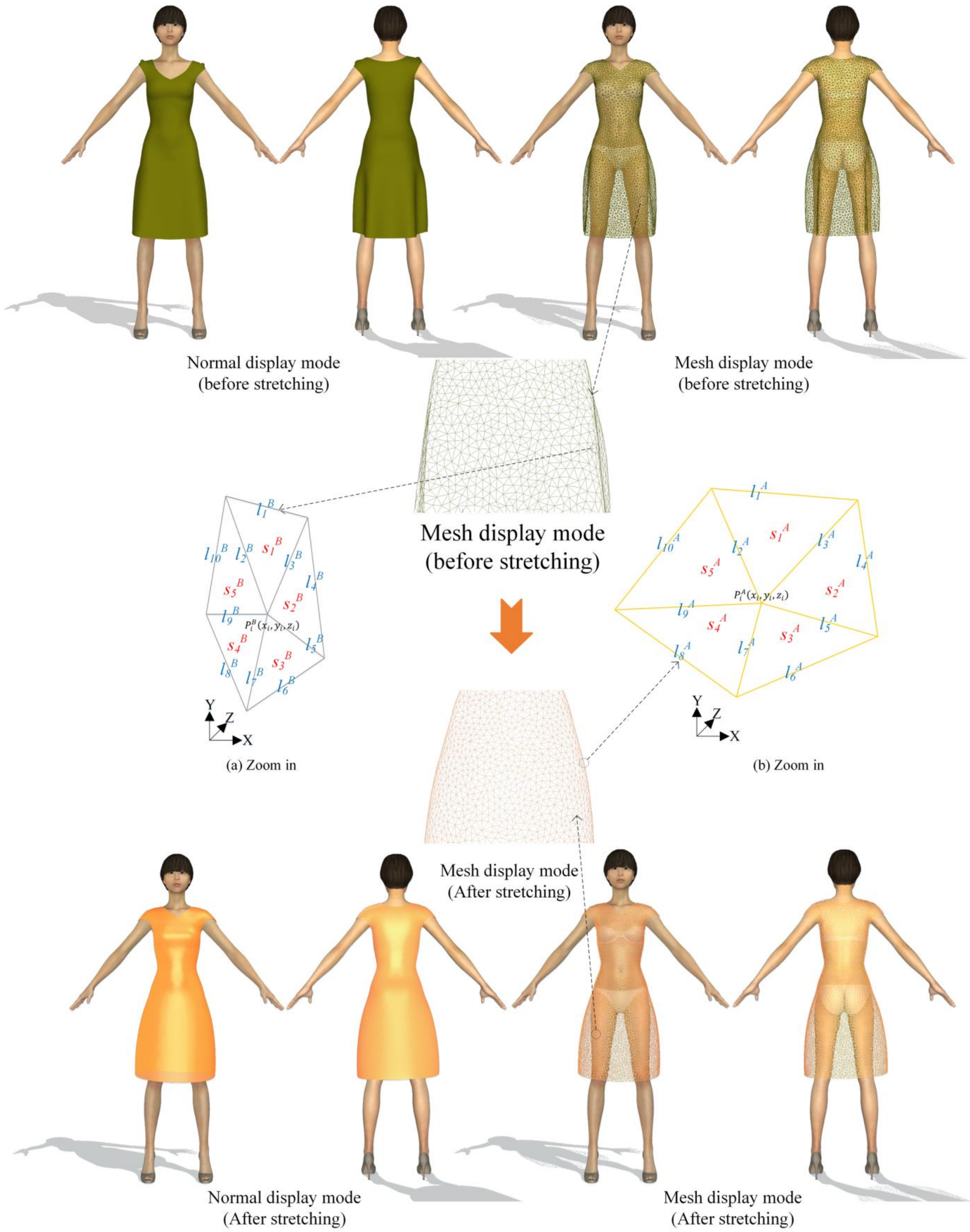


Figure 4-9 3D garment surfaces stretching and freezing.

In the previous steps, I constructed and adjusted a 3D garment surface (Figure 4-8). However, the 3D garment surface contains many creases and folds. The existence of these creases obstructs to draw construction curves precisely on the garment surface. In order to make construction curves or lines on the surface of the 3D garment conveniently and accurately, its surface should be as smooth as possible. As shown in Figure 4-9, I stretch and freeze the 3D garment surface in this step. The stretching rules of the 3D garment surface are given as follows:

$$l_i^B = l_i^A, (i = 1,2, \ldots, a) \text{ (rule of mesh edge invariance)} \quad (4\text{-}4)$$

$$s_i^B = s_i^A, (i = 1,2, \ldots, b) \text{ (rule of mesh area invariance)} \quad (4\text{-}5)$$

where l_i^B is the length of the ith triangular edge before stretching; l_i^A is the length of the ith triangular edge after stretching; s_i^B is the area of the ith triangular mesh before stretching; s_i^A is the area of the ith triangular mesh after stretching; a is the number of triangular edges of the 3D garment; b is the number of triangular meshes of the 3D garment.

According to 3D garment stretching rules (4-4) and (4-5), the 3D garment is stretched without changing area and edges for any triangular mesh. After that, I freeze the stretched garment for keeping the garment's shape. In our study, this processing is realized in the CLO 3D software environment. The final stretched and frozen 3D garment forms an OBJ format file and can be used in the following steps.

4.2.5 3D garment construction curves drawing

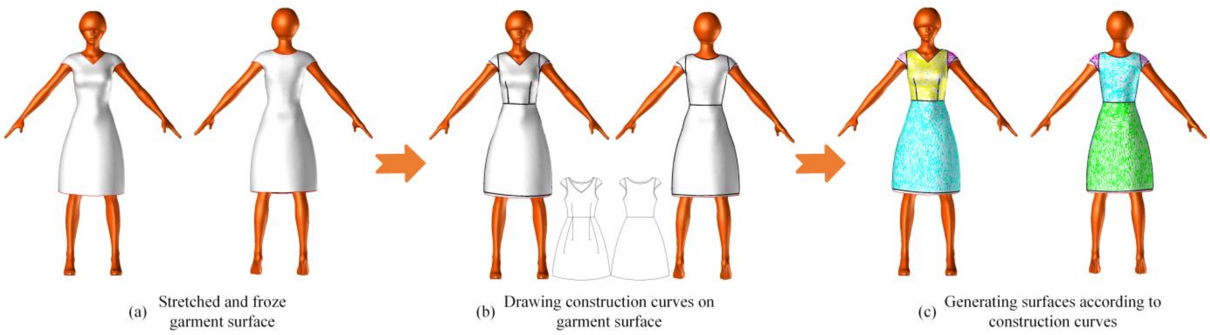
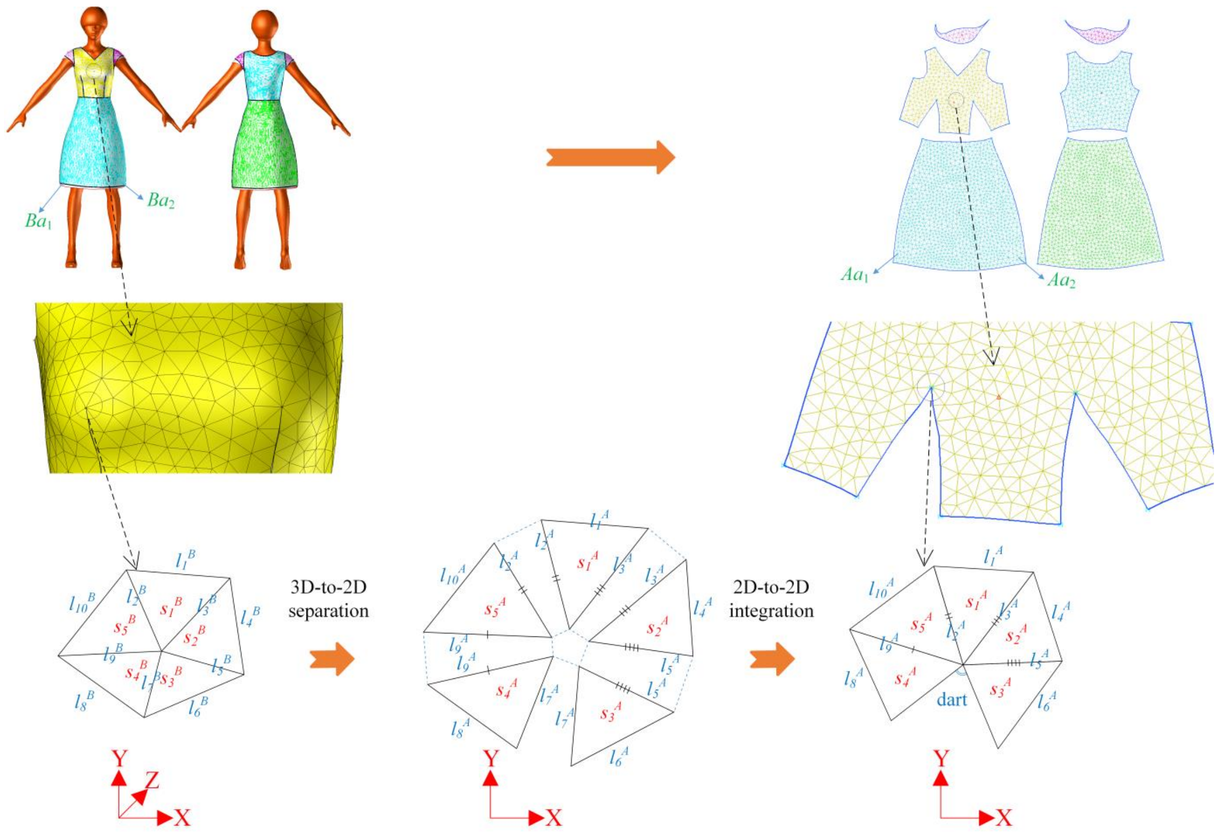


Figure 4-10 3D construction curves drawing and 3D garment surfaces generation.

In this step, I draw a number of construction curves on the stretched and frozen 3D garment surface according to the garment flat's internal lines by using the software DesignConcept of Lectra Company. These curves enable to divide the whole 3D garment surface into different regions. One example is shown in Figure 4-10.

4.2.6 3D surface unfolding



(a) Before unfolding (b) After unfolding

Figure 4-11 3D-to-2D patterns unfolding.

Based on the subdivided 3D garment regions, I unfold them to form 2D patterns (Figure 4-11). The unfolding rules of 3D garment surface are given as follows:

$$l_i^B \approx l_i^A \ (i = 1,2, \ldots, a) \text{ (rule of mesh edge approximation)} \tag{4-6}$$

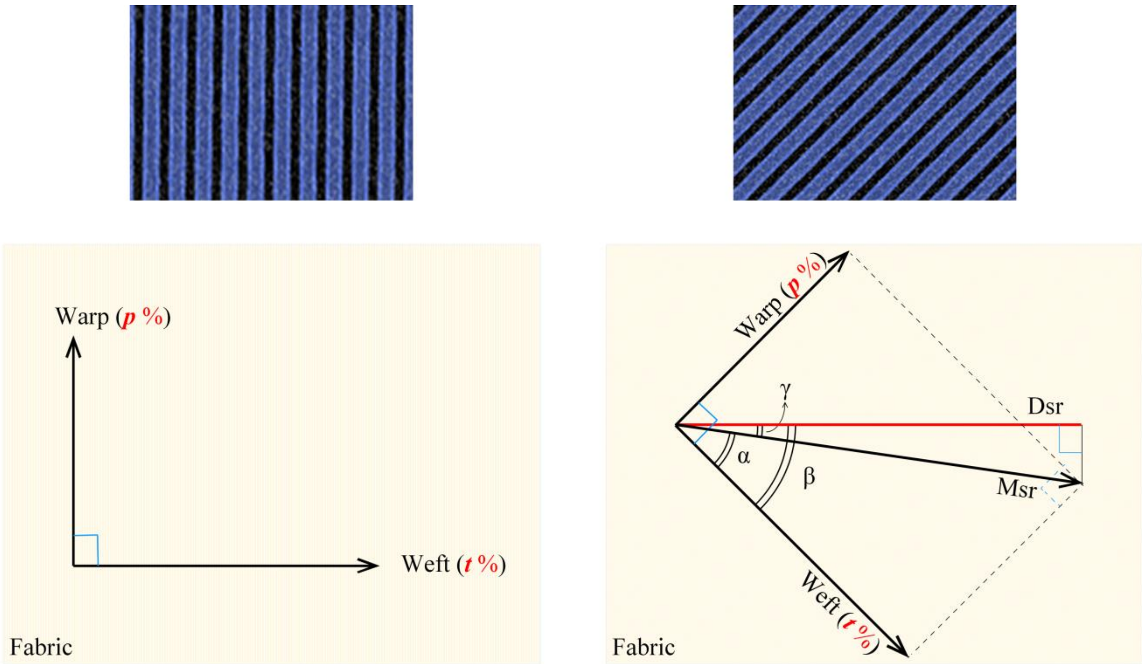
$$s_i^B \approx s_i^A \ (i = 1,2, \ldots, b) \text{ (rule of mesh area approximation)} \tag{4-7}$$

$$a_i^B = a_i^A (i = 1,2, \ldots, c) \text{ (rule of invariance for angle of intersecting curves)} \tag{4-8}$$

where l_i^B is the length of the ith triangular edge before stretching; l_i^A is the length of the ith triangular edge after stretching; s_i^B is the area of the ith triangular mesh before stretching; s_i^A is the area of the ith triangular mesh after stretching; a_i^B is the angle between two intersecting construction curves before stretching; a_i^A is the angle between two intersecting construction curves after stretching; a is the number of triangular edges of the 3D garment surface; b is the number of triangular meshes of the 3D garment surface; c is the number of angles of all intersecting construction curves.

Using 3D surface unfolding rules (4-6), (4-8) and (4-7), the changes of the areas and edges of the triangular meshes on the 3D garment surface should be minimized related to those of the corresponding 2D pattern. Also, the angles between all the intersecting construction curves on the garment surface should be invariant related to the 2D pattern.

4.2.7 2D garment pattern adjustment (post-processing)



(a) fabric weft and pattern weft are in the same direction (b) fabric weft and pattern weft are not in the same direction

Figure 4-12 Pattern adjustment with different fabric elasticities.

In the previous step, I do not consider the fabric elasticity in the process of 3D surfaces unfolding. However, this property is one of the important factors that affect the quality of garment pattern. The patterns generated by unfolding 3D surfaces should be shrunk according to fabric elasticity. As shown in Figure 4-12, I consider that the fabric warp-stretching and weft-stretching rates are p % and t % respectively. If the fabric and pattern' grain lines are in the same direction, the weft-stretching rate has no significant influence on pattern adjustment. Therefore, the patterns are only shrunk by t % in weft direction (Figure 4-12(a)). If the fabric and pattern' grain lines are not in the same direction, then the shrink rate Drs % of the patterns can be deduced as follows (Figure 4-12(b)):

$$\gamma = \beta - \alpha \tag{4-9}$$

$$\alpha = \arctan(p/t) \tag{4-10}$$

$$Msr = \sqrt{p^2 + t^2} \tag{4-11}$$

$$Dsr = Msr \times cos(\gamma) \tag{4-12}$$

where γ is the angle between integral direction and horizontal direction of a fabric; β is the angle between the weft direction and the horizontal direction of the fabric; Msr is the integral extensional ratio of the fabric; p and t are the fabric elasticity rates in warp and weft directions respectively; Dsr is the shrinkage rate of garment patterns.

By combing Formula(4-9) and Formula (4-10), the angle γ is obtained as follows:

$$\gamma = \beta - arctan(p/t) \tag{4-13}$$

By combining Formula (4-11), Formula (4-12) and Formula (4-13), Dsr is obtained as follows:

$$Dsr = \sqrt{p^2 + t^2} \times cos\left\{\beta - arctan\left(\frac{p}{t}\right)\right\} \tag{4-14}$$

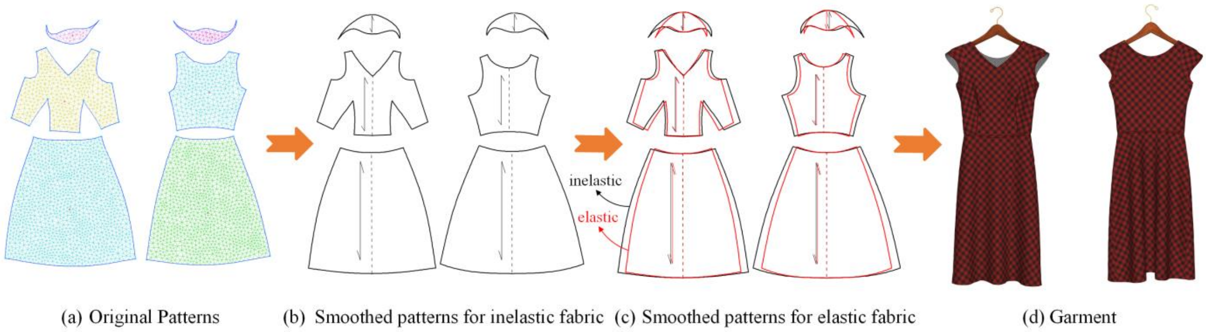


Figure 4-13 Garment pattern adjustment.

As shown in Figure 4-13(a), the 2D garment patterns generated by flattening 3D surfaces are only suitable for rigid (inelastic) fabric and their edges are too rough to make a garment. Thus, I first smooth these patterns' edges using the garment CAD software (Figure 4-13(b)) and then shrink the patterns according to Formula (4-15) (Figure 4-13(c)). Finally, the adjusted patterns can be used for production (Figure 4-13 (d)).

4.3 Application

Figure 4-14 Three application examples of 3DIGPMT.

3DIGPMT, integrating the previous design rules and the corresponding 3D garment CAD software, has been applied to pattern making of real industrial production. Three examples (jacket, pants, and dress) are shown in Figure 4-14. They represent the upper, lower, and one-piece clothing design respectively. The applications in Figure 4-14 indicate that the proposed method can be successfully adapted to design of various garment styles. The technology of 3DIGPMT does not require accurate outlines for extractions, meaning that both amateurs and professionals can easily handle and employ this method for their design work. More quantitative analysis of the method will be given in Chapter 6 in the frame of different design applications.

4.4 Discussion

Garment pattern making is the highest technical work in the process of clothing design and production. It links fashion design and clothing making [16]. Currently, pattern making is still a strongly experienced-based work. An effective pattern making method can improve garment products' development efficiency significantly. The 3D fashion design has shown its exceptional efficiency related to the traditional design methods. However, due to the low capacity of dealing with uncertain human knowledge in the 3D garment CAD environments, designers are trying both the traditional fashion design and 3D fashion design in a complementary way. The virtual try-on technology of 2D-to-3D can help designers to check whether the garment style is feasible, the 3D-to-2D flattening technology can help pattern makers to develop garment pattern, and the 3D-to-3D fashion design can help designers to design 3D garments. However, any technology mentioned previously cannot make fashion design more efficient if it is used alone. In this context, 3DIGPMT has been proposed to integrate the 2D-to-3D virtual try-on technology, the 3D-to-2D flattening technology and the 3D-to-3D fashion design together.

Actually, 3DIGPMT includes three processes: 2D-to-3D, 3D-to-3D and 3D-to-2D. The 2D-to-3D process uses the virtual try-on technology to roughly construct a 3D garment surface from garment flats. After that, the 3D-to-3D process uses the 3D garment transformation technology to adjust the 3D garment surface to meet the required design requirements. The 3D-to-2D process uses the flattening technology to flatten the constructed 3D garment surface into 2D patterns. Also, 3DIGPMT enables to set up interactions between the space of 2D patterns adjustment and the space of the 3D garment visualization in order to progressively adjust the 3D garment surface until the user's satisfaction. In this process, no professional knowledge is required. Even an amateur with design interests can apply 3DIGPMT to develop garment pattern rapidly after a short training. Due to the advantages of 3DIGPMT, pattern makers can develop garment pattern rapidly and effectively.

However, 3DIGPMT is not perfect because it cannot process complex interactions of fabrics/human bodies and complex styles. The pattern of the garment with complex styles cannot be easily developed by 3DIGPMT. Further research can be conducted along this direction.

4.5 Conclusion

In this research, the 3DIGPMT is proposed to generate garment patterns. The whole pattern making process is carried out in a 3D virtual environment. Compared to traditional pattern making methods or current methods of 3D garment pattern making, the proposed method has four advantages: 1) It enables to develop garment patterns through a series of interactions between the space of 2D pattern design and the space of 3D garment visualization without requiring special pattern making skills. 2) It is suited for both tight and loose garments. 3) Garment ease allowance, fabric elasticity, and draping are involved and considered in the proposed method. 4) The proposed method does not need trial and error, resulting in substantial cost reduction.

CHAPTER 5: MACHINE LEARNING-BASED GARMENT FIT EVALUATION TECHNOLOGY

Garment fit is not only one of the main factors influencing consumer's purchasing decision, but also strongly related to change or return after sales. In the apparel industry, it enables to connect garment design, production and sales. However, the traditional garment fit evaluation methods are usually time-consuming and require real try-on. Therefore, they are not fully adapted to fast fashion design and sales in an e-shopping context. In this chapter, I propose a Machine Learning-Based Garment Fit Evaluation Technology (MLBGFET) to evaluate remote garment fit without any real try-on. The proposed method can be applied in classical fashion design for reducing the number of real try-on and Internet-based collaborative fashion design and sales for integrating human comfort into the virtual garment fitting processes.

5.1 General principle and formalization

5.1.1 General principle

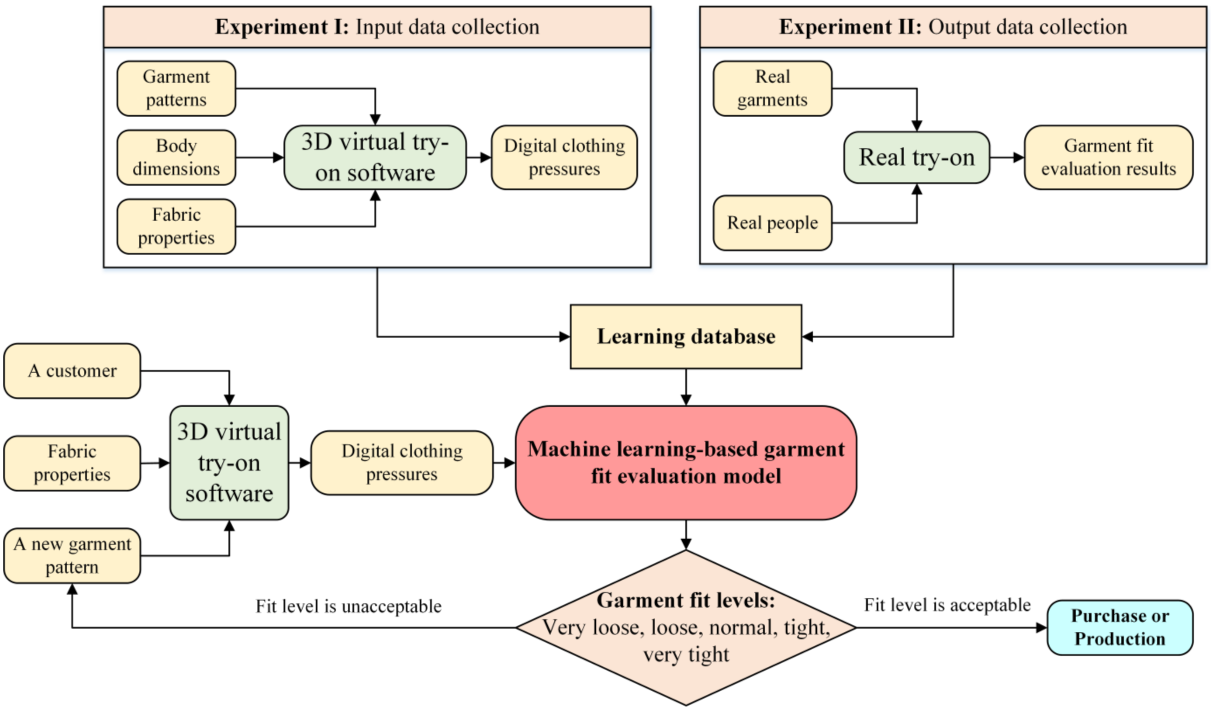


Figure 5-1 General scheme of MLBGFET.

The general scheme of MLBGFET is described in Figure 5-1. By using a commercialized 3D garment CAD software called CLO 3D developed by CLO Virtual

Fashion Inc., I can easily obtain the digital pressures for a specific body shape with a specific garment [52]. I consider that these digital pressures distributed on the whole virtual garment surface are close enough to the real pressures of the corresponding real garment surface on this body shape [47, 57-58]. By learning from the input data (digital pressures of virtual try-on) and output data (fit evaluation of real try-on) obtained from a set of real garments with different parameters, I set up a model characterizing the relation between the input and output variables, permitting to predict the fit evaluation from digital pressures of any new garment. This model enables to make interactions between the spaces of real and virtual garments in order to evaluate comfort of virtual products.

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, I do not need to precisely identify real clothing pressures. In fact, the previous research work has already shown that 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.) [47, 156-158, 57-58], but also are rather close each other in a certain range.

In the modeling approach, I have used different data learning techniques, including Naive Bayes, decision trees and artificial neural networks. The proposed models have been successfully applied in a real design scenario.

5.1.2 Formalization of the concepts and data

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

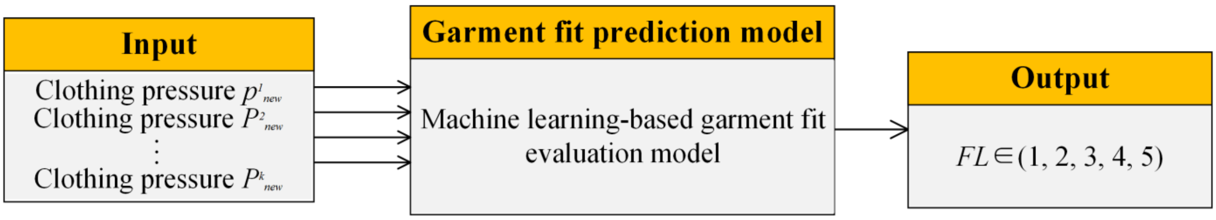


Figure 5-2 Modeling the relation between digital clothing pressures and garment fit level FL.

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

Let FL be the fit level of a garment, i.e. 1-very loose, 2-loose, 3-normal, 4-tight and 5-very tight.

Let $P_i = (p_i^1, \dots, p_i^j, \dots, p_i^k)$ 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 (I suppose that there exist k key positions on the whole garment surface). In a general case, the vector of digital pressures $P_{new} = (p_{new}^1, \dots, p_{new}^j, \dots, p_{new}^k)$ of a new garment g, is taken as input variables of the model.

5.2 Learning data acquisition

5.2.1 Preparation work for experiments

I 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 [52].

Table 5-1 Subjects and their corresponding 3D human body models' body dimensions distribution (unit: cm).

<table>
<tr><th>Measuring items</th><th colspan="9">Body dimensions</th></tr>
<tr><td>Height</td><td colspan="2">155.0</td><td colspan="3">160.0</td><td colspan="2">165.0</td><td colspan="2">170</td></tr>
<tr><td>Cervical height</td><td colspan="2">128.0</td><td colspan="3">136.0</td><td colspan="2">140.0</td><td colspan="2">144.0</td></tr>
<tr><td>Sitting cervical height</td><td colspan="2">58.5</td><td colspan="3">62.5</td><td colspan="2">64.5</td><td colspan="2">66.5</td></tr>
<tr><td>Arm length</td><td colspan="2">47.5</td><td colspan="3">50.5</td><td colspan="2">52.0</td><td colspan="2">53.5</td></tr>
<tr><td>Waist height</td><td colspan="2">92.0</td><td colspan="3">98.0</td><td colspan="2">101.0</td><td colspan="2">104.0</td></tr>
<tr><td>Bust</td><td colspan="2">75.0</td><td colspan="3">84.0</td><td colspan="2">88.0</td><td colspan="2">92.0</td></tr>
<tr><td>Neck girth</td><td colspan="2">32.0</td><td colspan="3">33.6</td><td colspan="2">34.4</td><td colspan="2">35.2</td></tr>
<tr><td>Shoulder</td><td colspan="2">37.4</td><td colspan="3">39.4</td><td colspan="2">40.4</td><td colspan="2">41.4</td></tr>
<tr><td>Waist girth</td><td>60</td><td>62</td><td>64</td><td>66</td><td>68</td><td>70</td><td>72</td><td>74</td><td>76</td></tr>
<tr><td>Hip girth</td><td>82.8</td><td>84.6</td><td>86.4</td><td>88.2</td><td>90.0</td><td>91.8</td><td>93.6</td><td>95.4</td><td>97.2</td></tr>
</table>

***Subjects*:** Nine female subjects with representative body shapes are selected for performing real try-on and body dimension measurement. Their body dimensions are shown in Table 5-1. 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 [159]. The corresponding 3D virtual body models used for virtual try-on are shown in Figure 5-3. (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).

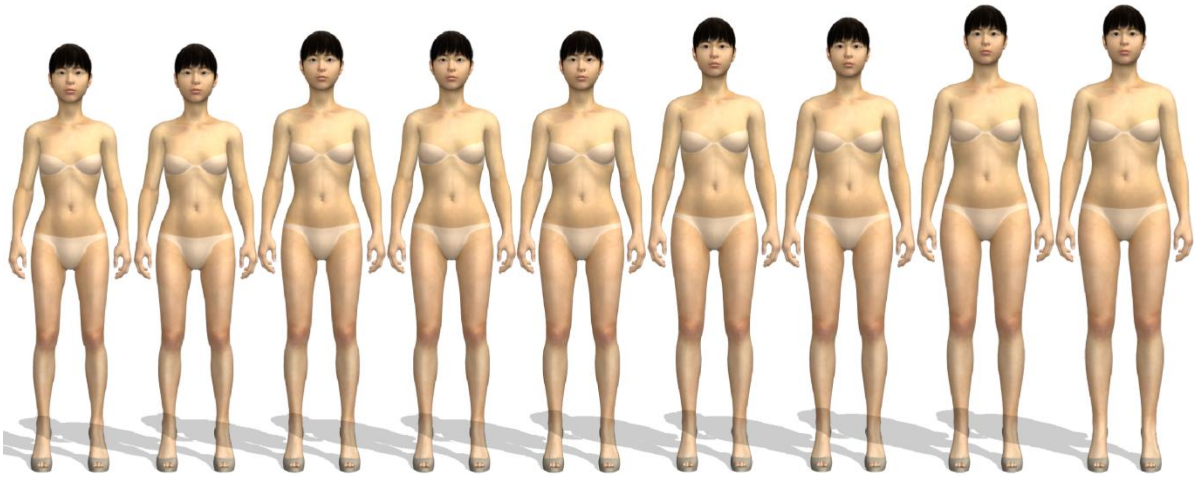


Figure 5-3 Nine virtual bodies used for virtual try-on generated based on the nine subjects.

Garments: 72 pairs of straight pants, which cover most of pants' sizes, are involved in the real try-on experiments for data collection (Table 5-2). These pants' fabric is shown in Figure 5-4. I select the pant type to test our proposed method because that they are the most challenging clothing item for a good fit [45]. If the proposed model predicts pants' fit accurately, this method could be also available for other styles.

Figure 5-4 The fabric used for pants making.

Table 5-2 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.

Table 5-3 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.

***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, I do not need to specially study the effects of fabric properties on garment fit. In Experiment II, I just selected a frequently used jeans fabric with the mechanical properties shown in Table 5-3 for making different garments of virtual try-on.

***Garment fit level*:** In this research, I classify all garment fit values into five levels (Figure 5-5). These fit levels are used in both real and virtual garment try-on.

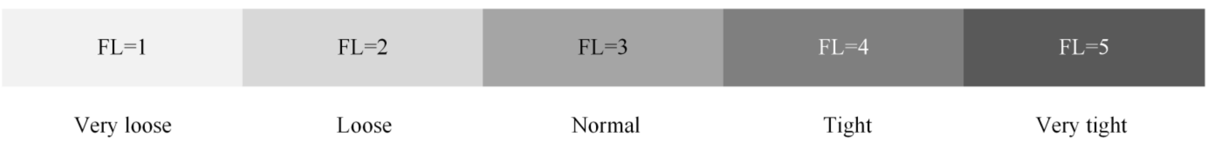


Figure 5-5 The proposed five garment fit levels.

***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 ℃。

5.2.2 Experiment I: Acquisition of the data on garment fit

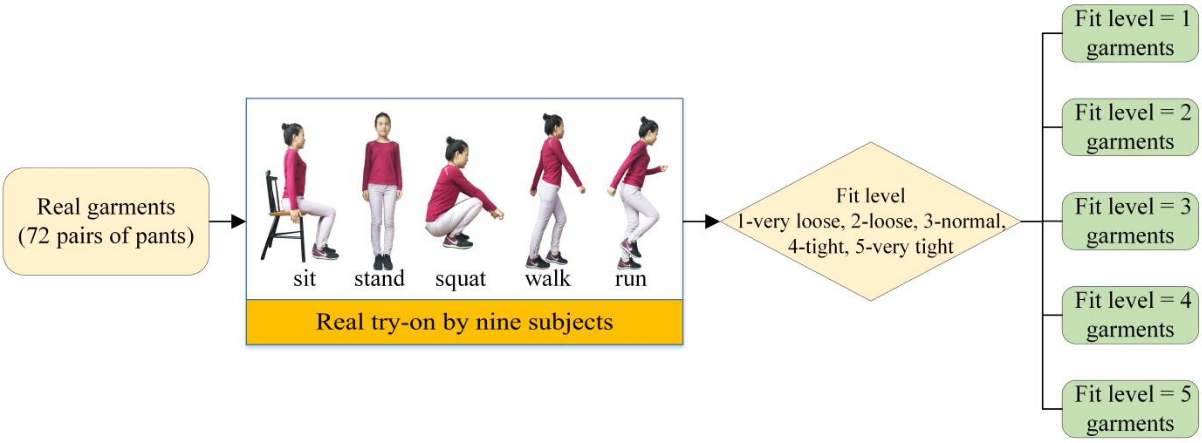


Figure 5-6 Garment fit data collection by real try on (Output learning data).

Table 5-4 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 5-5 Garment fitness data collected by real try-on (output learning data)

FL	Very loose			Loose			Normal			tight			Very tight		
	1	1	1	2	2	2	3	3	3	4	4	4	5	5	5
Sample No.	1	···	9	10	···	25	26	···	48	49	···	64	65	···	72

Note: the numbers of these samples are defined according to the evaluated fit levels from "very loose" to "very tight".

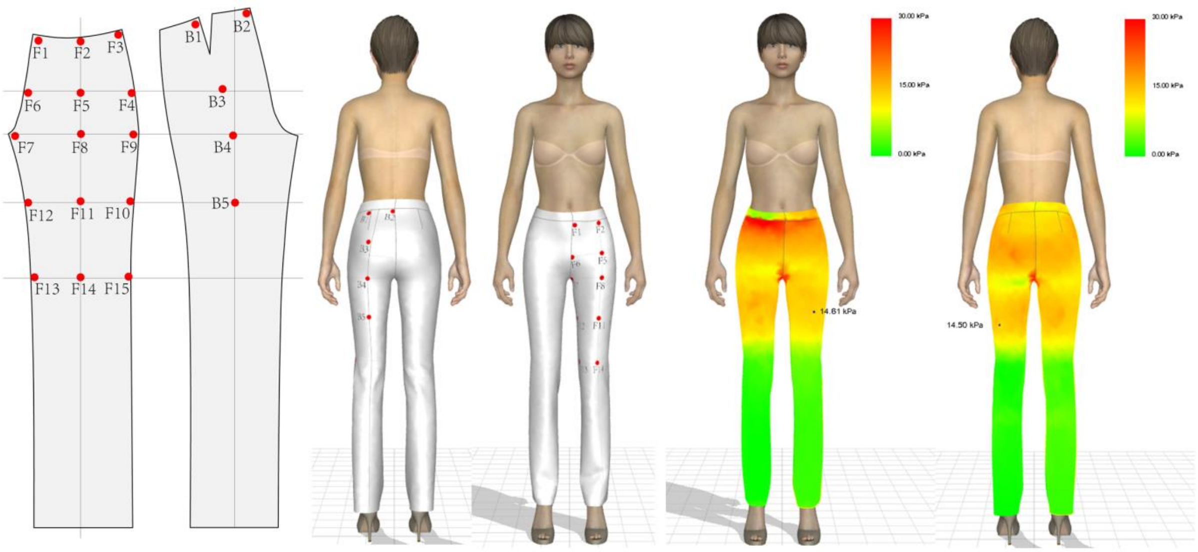
Experiment I is designed to evaluate garment fit levels using the real try-on. 72 pairs of pants are made according to the sizes in Table 5-2. The experiment procedure is shown in Figure 5-6. Nine selected female subjects with different body shapes (Figure 5-3) participate in the garment fit evaluation 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 5-4.

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 Figure 5-6). After that, she gives an overall fit level of the evaluated pants using one of the five scores in Figure 5-5.

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 very loose pants (9 pairs), the set of loose pants (16 pairs), the set of normal pants G_n (23 pairs), the set of tight pants G_l (16 pairs), and the set of very tight pants G_{vl} (8 pairs) (Table 5-5). The data will be taken as input learning data to build the proposed models.

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



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

Figure 5-7 Digital clothing pressure measurement by virtual try-on (Input learning data).

I design Experiment II to measure the digital clothing pressures at the key positions of the garment surface using the *CLO 3D* software (Figure 5-7). The concrete scheme of Experiment II is described as follows.

Step 1: I built nine 3D human models whose body dimensions are equal to those of the nine subjects (see Figure 5-3).

Step 2: I determine the key positions $F1, F2, \ldots, F15$ and $B1, B2, \ldots, B5$ of each pair of pants, which are uniformly distributed on the front piece pattern and on the back piece pattern respectively (Figure 5-7(a)). As the parts below knee have little effect on clothing fit, I do not define any key positions on them.

Step 3**:** According to Table 5-4, I 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 (Figure 5-7(b) and Figure 5-3).

Step 4**:** I measure the digital clothing pressures of each pair of pants on predefined 20 key positions of each garment during its virtual try-on (Figure 5-7 (c)).

The digital clothing pressure data of the 72 pairs of pants are shown in Table 5-6. 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 Figure 5-2.

Table 5-6 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 5-5; $F1$, $F2$,…, $B5$ refer to the key positions of the digital clothing pressures, shown in Figure 5-7 (a) and Appendix 3. The virtual try-on and digital clothing pressures measurement are carried out by CLO 3D software developed by CLO Virtual Fashion Inc.

5.3 Modeling the relation between clothing pressures and garment fit level

In chapter 2, I have already introduced the advantages of Naive Bayes, Back Artificial Neural Networks (BP-ANN) and Decision tree with C4.5. In this section, the three algorithms are applied respectively to model the relation between digital clothing pressures and garment fit levels.

5.3.1 Modeling with Naive Bayes

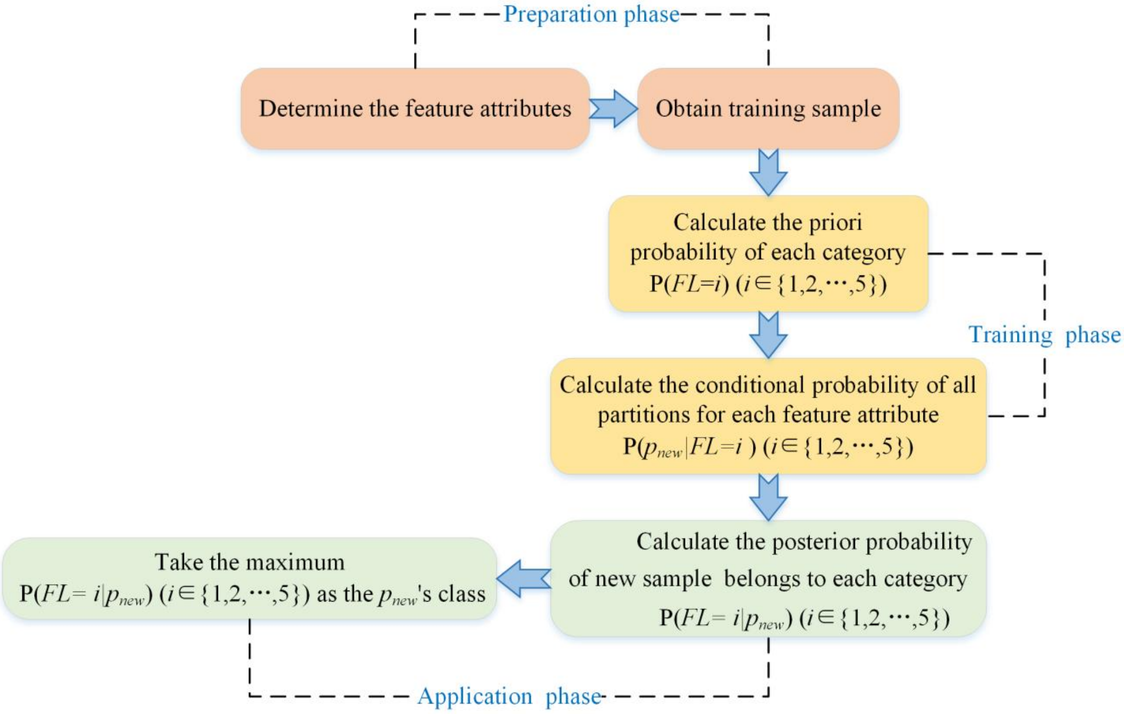


Figure 5-8 Modeling with Naive Bayes.

As a classical tool for modeling with data learning, the Naive Bayes classifier is first used in our approach for constructing the garment fit evaluation model. Based on the general principle presented in Chapter 2, I present the specific modeling procedure in Figure 5-8. It is composed of the following six 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, I 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.

According to Figure 5-5, I have five levels of garment fit (categories). Thus, the prior probability of each category i ($i \in \{1, \dots, 5\}$) can be:

$$P(FL = i) = \frac{the\ number\ of\ fit\ evaluations\ corresponding\ to\ the\ i - th\ level}{the\ total\ number\ of\ fit\ evaluations} \quad (5\text{-}1)$$

Step 4: Calculating the conditional probability of all partitions for each feature attribute.

$$P(P_{new}|FL = i) = \prod_{j=1}^{k} P\left(p_{new}^{j}/FL = i\right) \quad (5\text{-}2)$$

Step 5: Calculate the posterior probability of new sample P_{new} belongs to each category.

$$P(FL = i|P_{new}) = \frac{P(FL = i)P(P_{new}|FL = i)}{\sum_{i=1}^{5} P(FL = i)P(P_{new}|FL = i)} \quad (5\text{-}3)$$

Step 6: Predicting with Naive Bayes classifier.

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

If $P(FL = l|P_{new}) = \max_{1 \le i \le 5}\{P(FL = i|P_{new})\}, (l \in \{1,2, \dots ,5\})$, then the new sample P_{new} corresponds to the fit level l.

5.3.2 Modeling with BP-ANN

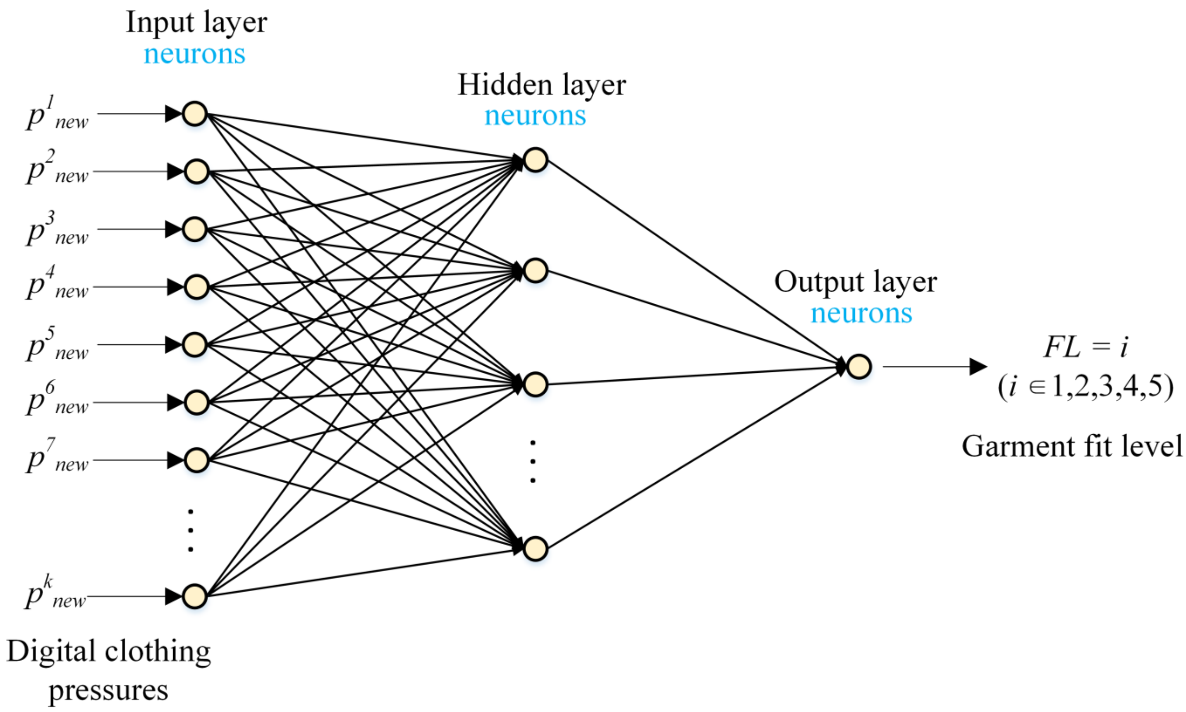


Figure 5-9 Modeling with BP-ANN.

BP-ANN is also applied to model the relationship between digital clothing pressures and garment fit level (Figure 5-9). The model construction includes BP-ANN parameters setting, BP-ANN training and BP-ANN prediction.

Step 1: BP-ANN parameters setting

Network layer setting

It has been proved that any continuous function can be uniformly approximated by a BP network model with only one hidden layer [160-161]. As our problem is rather simple (20 inputs, 1 output and nonlinear continuous relationship), the BP-ANN 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 network. 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 network acts 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-ANN prediction accuracy. If this number is too small, the ability of learning from data in the network 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 [161]. 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 [162]. Its value is 10.

Learning rate

Learning rate has an important effect on the performance of the BP neural network. 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 network can learn quickly, but easily lead to a wrong convergence [160]. 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.

Step 2: BP-ANN training [163]

Actually, BP-ANN training process is a process for the connection weights adjustment. The principle of weights adjustment has been described in Section 2.4.2. It mainly contains the following nine stages:

1) Initialize of the connection weights of the network.

2) Select a sample from the training dataset as the input of the network.

3) Calculate the output value of the network.

4) Calculate the error of the network 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.

Step 3: BP-ANN prediction

After identifying the connection weights by the previous training step, the proposed model in Figure 5-9 can be used to predict garment fit level by inputting the measured digital clothing pressures of a new garment.

5.3.3 Modeling with decision tree C4.5

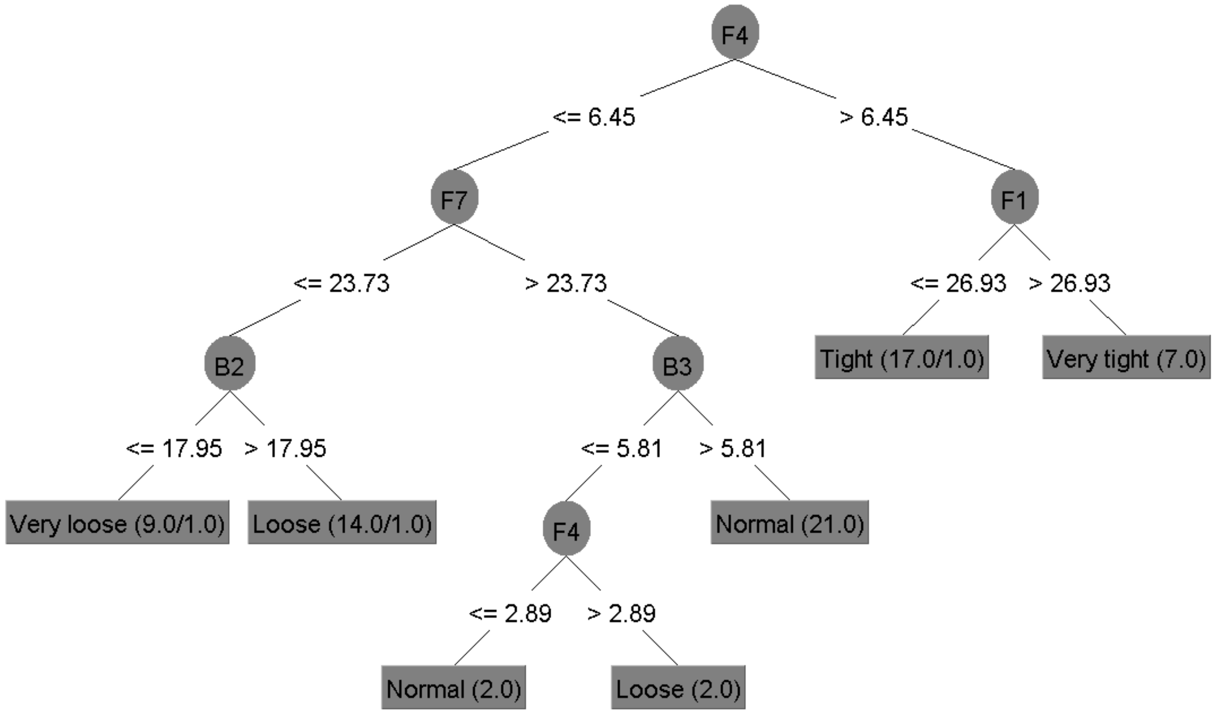


Figure 5-10 Decision tree generated by C4.5 algorithm for garment fit prediction.

A decision tree with C4.5 algorithm is also applied to model the relation between the digital clothing pressures and garment fit. The modeling procedure with the C4.5 decision tree is composed of the following four steps：

Step 1: Computing the information gain rate

The digital clothing pressures are all continuous attributes. Thus, they should be first discretized. Then, I calculate the information gain rate of all the attributes (i.e. pressures at the key positions). The attribute with the highest information gain rate is chosen as the attribute of the root node. More details can be found in Section 2.3.

Step 2: Building the decision tree

The root node permits to separate the range of the corresponding attribute into several classes or branches. For each branch, by using the same method (selecting the attribute with the largest information gain rate and branching), I obtain new tree branches at the lower level. This procedure repeats until all the samples in any branch node belong to the same class. These terminal nodes are taken as leaves.

Step 3: Tree pruning

The decision tree is pruned in order to eliminate the influence of random factors such as noises and isolated points, A concise and simplified decision tree can be obtained. The decision tree with C4.5 adopts the post-pruning algorithm.

Step 4: Decision tree prediction[164]

The decision rules can be directly obtained from the generated decision tree. Both decision tree and decision rules can be used to classify and forecast the new data set.

According to the above four steps, I use the data collected in Experiments I and II to generate a decision tree (See Figure 5-10). It can be interpreted as follows. The most relevant digital pressure is located at the position $F4$ (side waist-hip). The secondary relevant pressures are located at the positions $F1$ (front waist) and $F7$ (crotch). Seven rules can be extracted from the decision tree. One example is: If $F4 > 6.45$ and $F1 > 26.93$, then Fit Level is very tight. All these results conform to human knowledge of experts. I find that the results extracted from a decision tree are very intuitive and easy for interpretation.

5.4 Model validation

Table 5-7 Comparison of prediction accuracy between the three models and traditional methods

Prediction methods		Prediction Accuracy
Machine learning-based methods	Naive Bayes	80.6%
	BP-ANN	83.3%
	Decision tree C4.5	81.9%
Traditional methods	—	Less than 50%

Note: The prediction accuracies are calculated by the K-fold cross validation (k = 10).

In this section, I will compare the performances of the previous three garment fit evaluation models, i.e. Naive Bayes, BP-ANN and C4.5 by predicting the level of fit FL_{new} of a series of new garments according to the corresponding measured digital clothing pressures of $P_{new} = \left(p_{new}^1, \dots, p_{new}^j, \dots, p_{new}^k\right)$.

The input and output data for setting up the model are found in Table 5-6 and Table 5-5 respectively. In order to obtain more reasonable validation result, I 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 [165]. 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 BP-ANN model is with the highest prediction accuracy, the performance of the decision tree with C4.5 algorithm is the second and Naive Bayes model is the third (Table 5-7). All of these models have a good performance in accuracy ($> 80\%$). Even for the worst case, i.e. the Naive Bayes model, its accuracy is also larger than 80%. Obviously, the machine learning-based garment fit evaluation approaches are better than the traditional methods currently used in garment companies ($< 50\%$) [66-68].

5.5 Discussion

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

In Chapter 1, I have pointed out that the ease allowance between a garment and the human body is not a good indicator of reflecting garment fit. Therefore, I 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 [57-58]. Our previous research shows that the digital clothing pressures can reflect garment wear comfort accurately [57]. It is for this reason that I select the digital clothing pressures as a key indicator for performing remote garment fit prediction without real try-on. In practice, 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, I 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 digital and real clothing pressures are strongly correlated [57] and close enough in a certain range. The training and prediction of the proposed fit evaluation models are both based on digital clothing pressures and do not involve any real clothing pressures. So, even if the real clothing pressures and digital clothing pressures have some differences, the prediction accuracies of the proposed models are not affected.

5.5.2 Application prospect

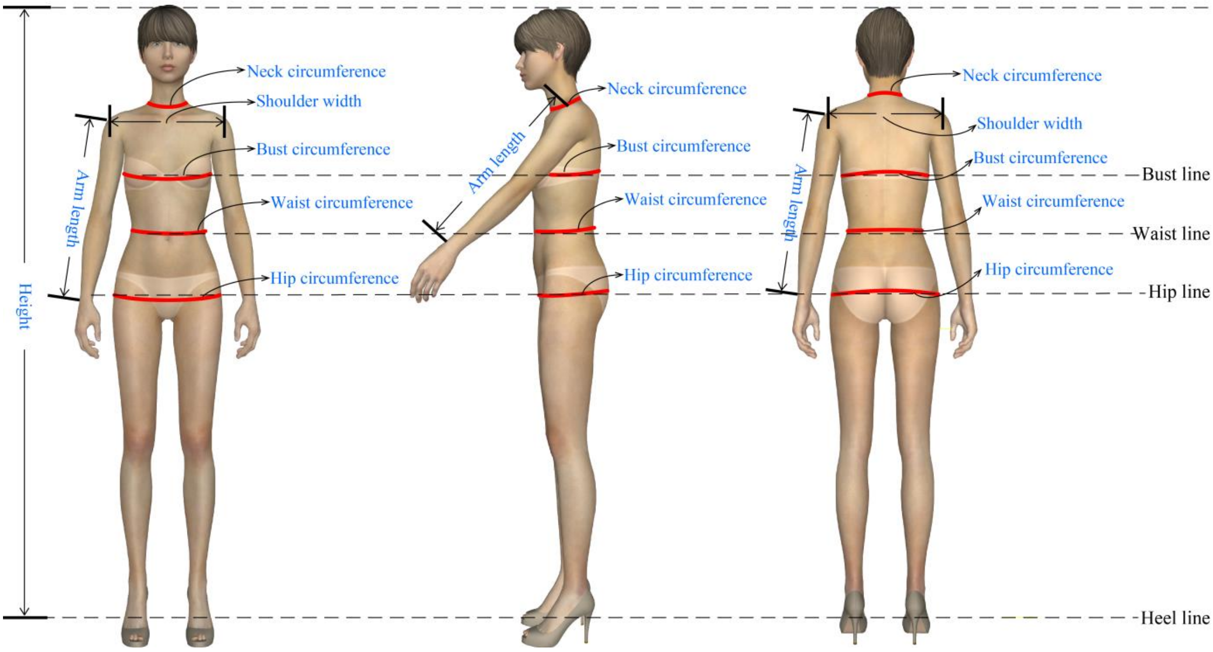


Figure 5-11 Legend of anthropometric measurement.

The study of remote fit prediction is extremely significant for online garment shopping because it directly has impacts on consumer's decisions of garment purchasing [59-62]. Thus, high accuracy of garment fit prediction can decrease the rates of returns and exchanges significantly. Traditional garment fit evaluation methods are less efficient for e-shopping because they strongly require involvement of designer's personal experiences and preferences. Therefore, people who do not master expert knowledge cannot easily use the traditional methods for evaluating garment fit. Also, for the companies managing with massive garment online transactions, thousands of garments can be purchased within a very short time. The fit evaluation work load will be too heavy if each garment fit is evaluated using traditional methods. In this context, I proposed three machine learning-based models for quantitatively characterizing the relationship between measured digital clothing pressures and fit levels. The construction of the proposed models is based on learning from the experimental data collected during virtual and real garment try-on. Compared with the traditional garment fit evaluation methods, the most important advantage of the proposed method is that it can predict garment fit rapidly and automatically without any real try-on and designers' involvement. It cannot only meet the garment e-shopping demands but also be integrated into the PDM (Product Data Management) system of the company for optimizing the process of garment product development.

When applying the proposed method to a design process, the customer should first provide his/her body dimensions. These dimensions are used to construct a 3D human model for a virtual try-on. These body dimensions are collected with a 3D body scanner. If this device is not available, the measurement of body dimensions can be realized manually at the key positions. Concretely, for garment design on an upper body, the customer should provide arm length, shoulder width, neck circumference, waist circumference, bust circumference and height. For garment design on a lower body, the customer should provide waist circumference, hip circumference and height (see Figure 5-11).

5.5.3 Limitation and future research

In our study, I do not consider the influence of garment styles and fabric properties on fit levels because they have been taken into account in the digital clothing pressures measured in the 3D garment CAD environment. As already mentioned in Chapter 1, the concept of "fit" studied in my thesis only deals with comfort feeling of garments caused by garment sizes. Here I do not discuss the aesthetic effects in a garment fitting. Further research can be carried out in this direction.

Due to the time limitation of my thesis, some work done is too simplified. For example, during the real try-on, I only evaluate the overall fit level for all the gestures and all the positions. In fact, more accurate results can be obtained if I propose to evaluate a series of local fit levels (hip fit level, waist fit level, …) 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.

Moreover, the accuracy of the proposed models (between 80% and 85%) can be further increased by measuring dynamical digital clothing pressures for a series of gestures during the virtual try-on. It means that the static clothing pressure at each key position will be transformed into a time series characterizing the variation of the pressure at this position during the movement. In this situation, all simultaneous pressures can be considered in the input variables of the models.

5.6 Conclusion

In this research, I propose three garment fitting prediction models based on the techniques of Naive Bayes, BP-ANN and decision tree C4.5 respectively. Compared with the traditional garment fit evaluation methods, MLBGFET has a number of obvious advantages: 1) rapidity and automatic processing 2) independence of any real try-on; 3) removal of human involvement; 4) continuous improvement of the model's performance with new learning data.

Based on the analysis of different intelligent algorithms, I consider that the model of neural networks with Back-Propagation Learning Algorithm is more adapted to big companies for constructing a garment fit evaluation model because they generally master a great quantity of data for learning, and the model of decision trees can be more adapted to small companies because they generally have a few quantity of data and the requirement for prediction accuracy is not high.

CHAPTER 6: APPLICATIONS OF KNOWLEDGE-BASED GARMENT DESIGN AND FIT EVALUATION SYSTEM

In general, the process of garment design and fit evaluation requires designers to master abundant experience and knowledge. For a young inexperienced designer, it is difficult to develop satisfying garment products. The performance of a clothing company and a fashion brand is strongly related to the personal quality of the associated fashion designers and pattern makers. In practice, the existence of uncertain human factors is not favorable for the sustainable development of textile/fashion enterprises. In this chapter, I give four applications of the proposed knowledge-based garment design and fit evaluation (KBGDFE) system by combining the three technologies presented in the previous chapters. I wish to show how these technologies are used for development of new design processes in classical and online environments, leading to more systematic and more reliable garment products.

6.1 General scheme

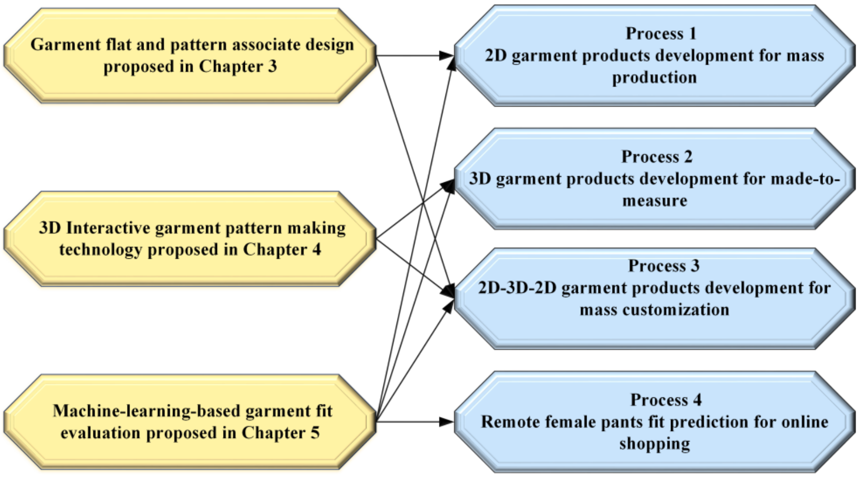


Figure 6-1 General scheme of the applications of knowledge-based garment design and fit evaluation system.

The general scheme about the applications of the proposed system is described in Figure 6-1. Some details are given below.

- The first application, applying both GFPADT proposed in Chapter 3 and MLBGFET in Chapter 5, deals with associated design and evaluation of patterns for mass production. With the help of the proposed system, garment products can be developed simultaneously and automatically.

- The second application, utilizing both 3DIGPMT proposed in Chapter 4 and MLBGFET proposed in Chapter 5, is a process of garment development for made-to-measure. With the help of the proposed system, new garments can be designed in order to be adapted to different personalized body sizes and shapes.
- The third application, using GFPADT proposed in Chapter 3, 3DIGPMT proposed in Chapter 4 and MLBGFET proposed in Chapter 5, is a process of 2D-3D-2D customized garment products development for mass customization.
- The fourth application is a remote garment fit prediction for online shopping. With the help of the data learning-based models proposed in Chapter 5, I evaluate garment fit from digital pressures measured during the virtual fitting process without any real try-on.

6.2 Application 1: 2D garment products development for mass production

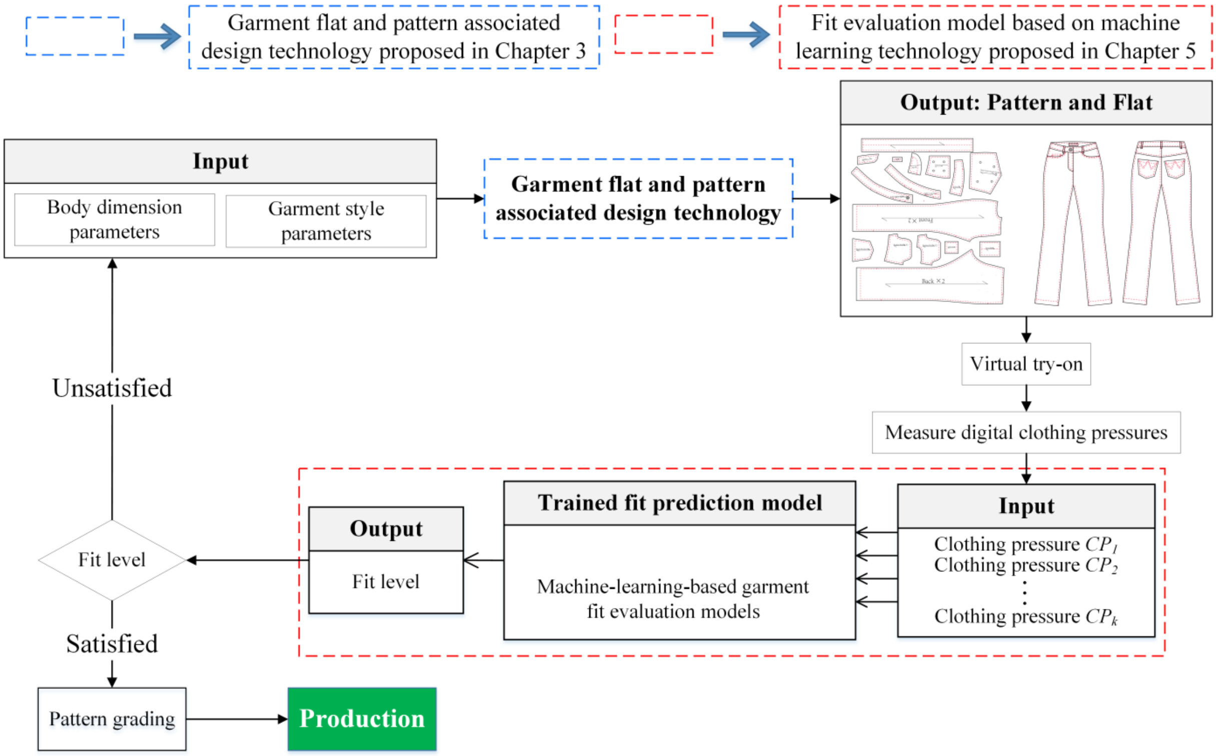


Figure 6-2 Process 1: 2D garment products development for mass production.

In this application, I introduce a new design process using both GFPADT and MLBGFET, proposed in Chapters 3 and 5 respectively, for helping pattern makers to quickly develop garment patterns in the context of mass production (Process 1).

As shown in Figure 6-2, a pattern maker inputs the body dimensions of a specific customer and the selected garment style to the associated design system developed in

Chapters 3 (see blue wireframe in Figure 6-2). Based on these inputs, this system generates the garment flats and their associated patterns automatically. Using the method proposed in Figure 5-7, the garment digital pressures are measured on the predefined key positions. Then, the machine learning-based garment fit evaluation model is used for predicting the garment fit automatically (see red wireframe in Figure 6-2). If the predicted fit level shows that the garment is acceptable, the garment patterns will be sent to the production department for pattern grading. Otherwise, the pattern maker will further modify the patterns of the unsatisfied garment until the final satisfaction (Figure 6-2).

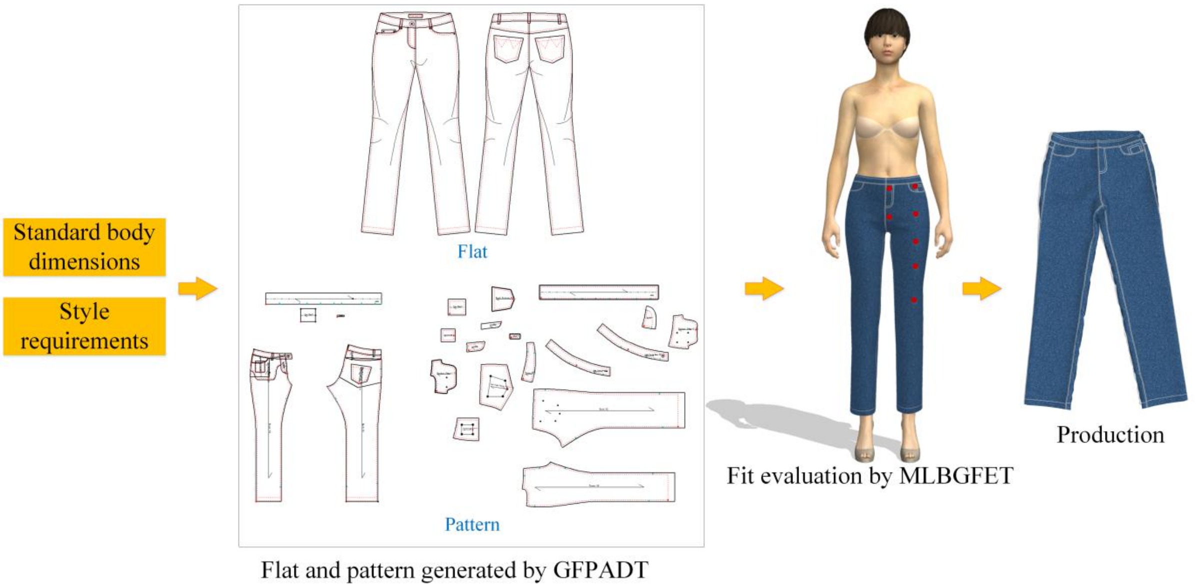


Figure 6-3 Pants development using GFPADT and MLBGFET.

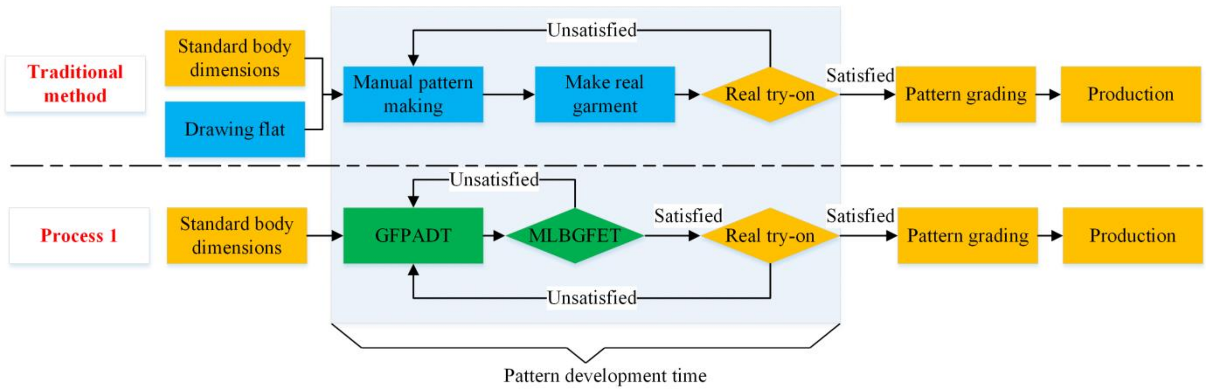


Figure 6-4 Traditional pattern making and Process 1 for pants mass production.

I make a pair of pants using the method of Process 1 (See Figure 6-3 for the results) and the traditional method respectively. Next, I compare these two methods. As shown in Figure 6-4, the differences between these two methods exist in three aspects: flat drawing time, pattern making time and the number of real try-on. For pant pattern development, Table

6-1 shows that Process 1 in Figure 6-2 is much better than the traditional method. The flat drawing time is decreased from 0.5 hour to 0.1 hour, the pattern development time from 5 hours to 3.5 hours and the number of real try on from 7 to 4.

Table 6-1 Comparison between the traditional method and Process 1

Methods of mass production	Flat drawing time (hours)	Pattern development time (hours)	The number of real try-on
Traditional method	0.5	5	7
Process 1	0.1	3.5	4

Note: the result only refers to the pant type. Other style garments may be different.

6.3 Application 2: 3D garment products development for made-to-measure

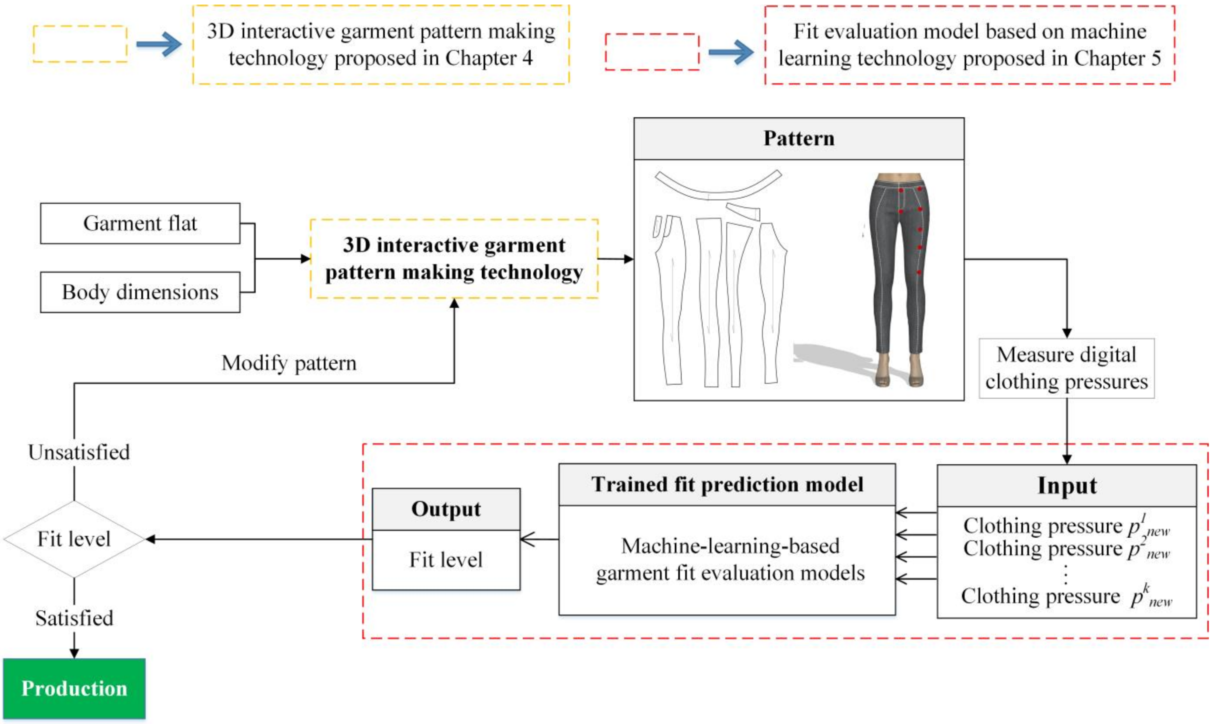


Figure 6-5 Process 2: 3D garment products development for made-to-measure.

For a garment company, made-to-measure can be more popular if the prices of customized garments are further reduced. In this section, I introduce a new design process based on 3DIGPT and MLBGFET proposed in Chapters 4 and 5 respectively for developing customized garment products (Process 2). As shown in Figure 6-5, a fashion designer draws garment flats according to the requirements of a customer. Meanwhile, a 3D body scanner extracts the 3D point cloud data of his/her body surface. Next, the corresponding personalized 3D human model is built using the collected 3D point cloud data. Then, 3DIGPMT proposed in Chapter 4 is applied to develop garment patterns on the personalized 3D human model.

Finally, digital clothing pressures are measured using the method proposed in Figure 5-7. After the previous operations, the collected digital clothing pressures are input to the fit evaluation model in order to predict the garment fit automatically (see red wireframe in Figure 6-5). If the predicted fit evaluation result is acceptable, the garment pattern will be sent to the production department. Otherwise, the pattern maker will modify the garment until the final satisfaction (Figure 6-5).

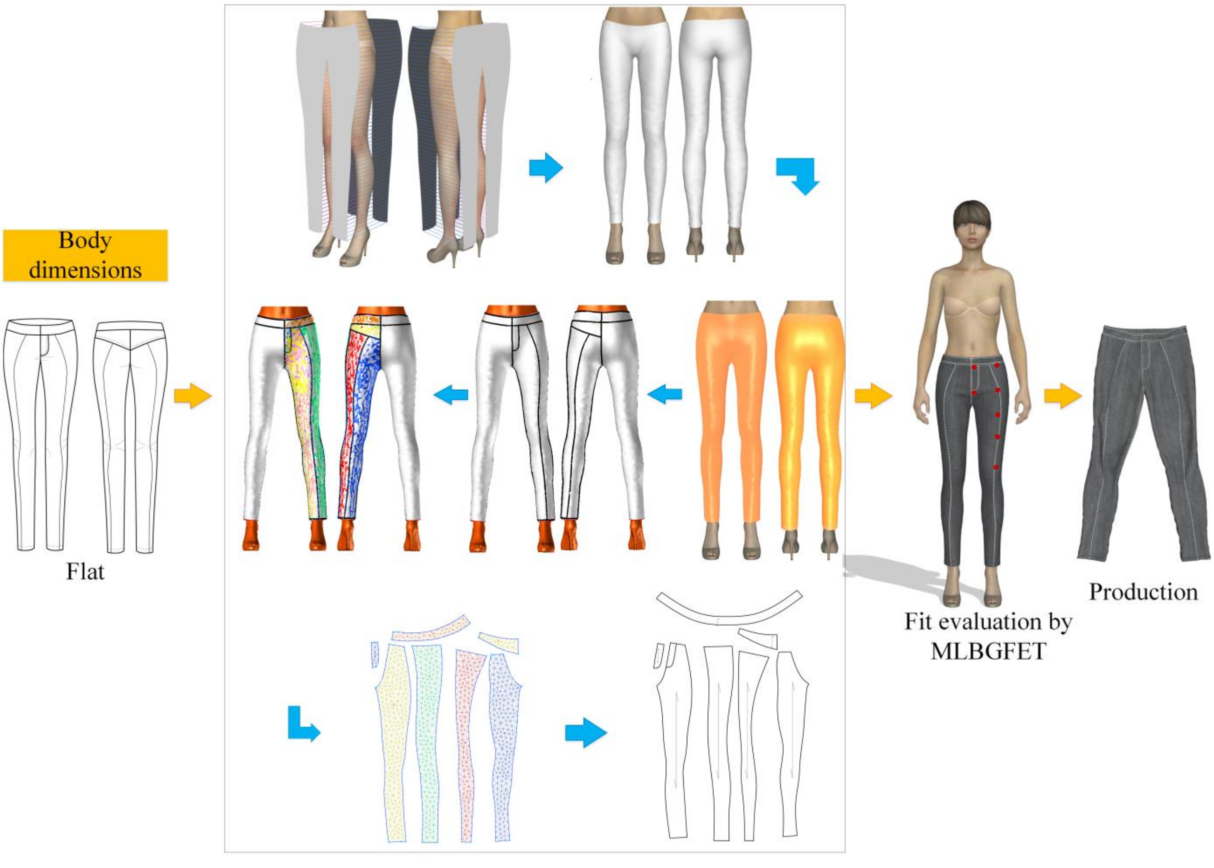


Figure 6-6 Pants development using 3DIGPMT and MLBGFET.

I make a pair of pants using Process 2 (See Figure 6-6 for the results) and the traditional method respectively and then compare between them. As shown in Figure 6-7, the differences between these two methods are mainly in the following three aspects: 3D human body adjustment time, pattern making time and the number of real try-on. For pant pattern development, Table 6-2 shows that Process 2 in Figure 6-5 is also better than the traditional method. Although the time of 3D human body adjustment is increased by half an hour, the pattern development time of Process 2 can be reduced by 2.5 hours, and the number of real try-on from 7 to 4.

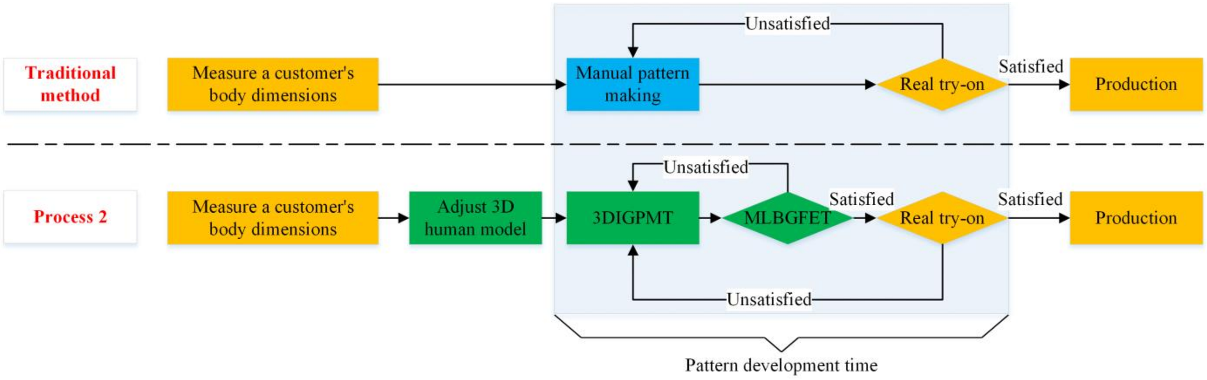


Figure 6-7 Traditional pattern making and Process 2 for pants made-to-measure.

Table 6-2 Comparison between the traditional method and Process 2

Methods of made-to-measure	3D human body adjustment time (hours)	Pattern development time (hours)	Number of real try-on
Traditional method	0	7	7
Process 2	0.5	4.5	4

Note: the result only refers to the pant type. Other style garments may be different.

6.4 Application 3: 2D-3D-2D garment products development for mass customization

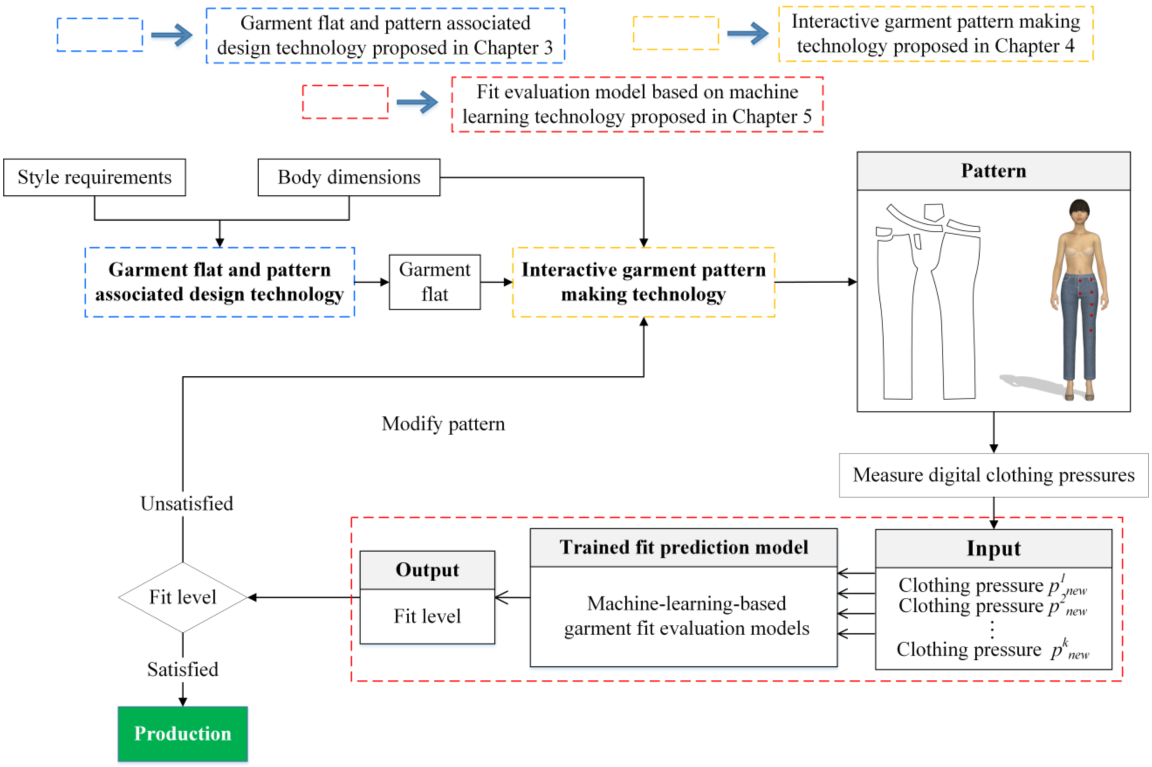


Figure 6-8 Process 3: 2D-3D-2D garment products development for mass customization.

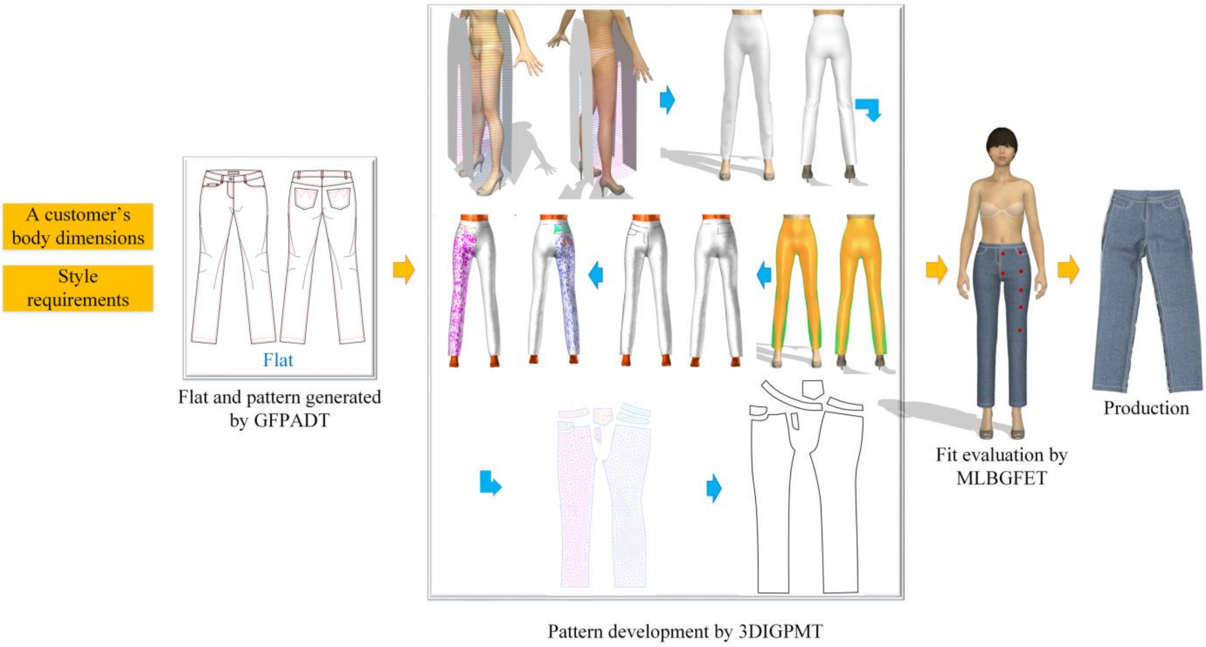


Figure 6-9 Pants development using GFPADT, 3DIGPMT, and MLBGFET.

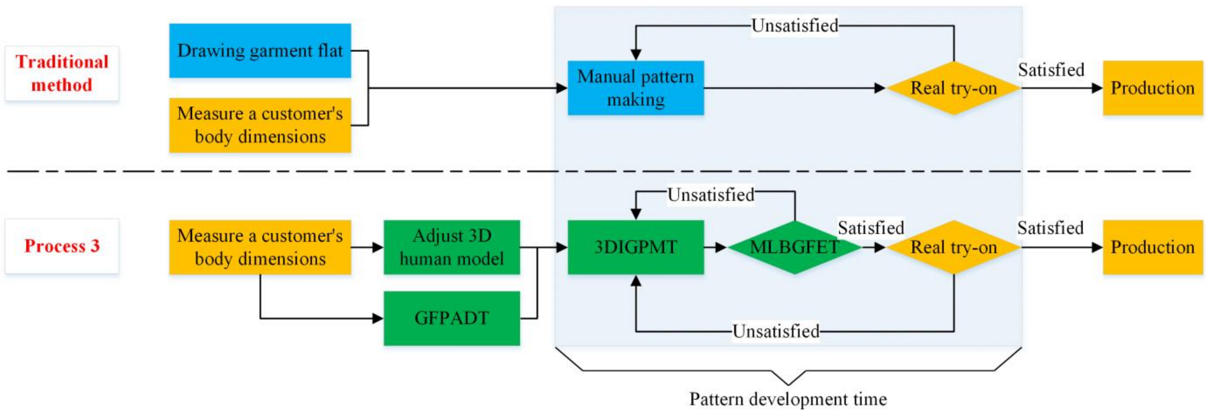


Figure 6-10 Traditional pattern making and Process 3 for pants mass customization.

In this application, I introduce a new design process using GFPADT, 3DIGPMT and MLBGFET, proposed in Chapters 3, 4 and 5 respectively, for helping pattern makers to develop garment patterns rapidly in the context of mass customization (Process 3). As shown in Figure 6-8, a garment flat is generated automatically by inputting style requirements and body dimensions to the associated design system developed based on GFPADT. Then, pattern makers make garment patterns using 3DIGPMT. After that, MLBGFET is applied to evaluate the garment fit level. If the predicted fit level shows that the garment is acceptable, the garment patterns will be sent to the production department. Otherwise, the pattern maker will further modify the unsatisfied garment's 3D patterns until the final satisfaction (Figure 6-8).

I make a pair of pants using Process 3 (See Figure 6-9 for the results) and the traditional method respectively and then compare them. As shown in Figure 6-10 , the differences between these two methods are in the following four aspects: flat drawing time, 3D human body adjustment time, pattern development time and the number of real try-on. For pant pattern development, Table 6-3 shows that the total time of these two methods have no obvious difference. However, the number of real try-on of Process 3 is reduced from 4 to 2 compared with the traditional method. A fewer number of real try-on means a decrease of cost and time for garment making.

Table 6-3 Comparison between the traditional method and Process 3

Methods of mass production	Flat drawing time (hours)	3D human body adjustment time (hours)	Pattern development time (hours)	Real try-on times
Traditional method	0.5	0	2.5	4
Process 3	0.1	0.5	2.5	2

Note: the result only refers to the pant type. Other style garments may be different.

6.5 Application 4: Remote female jeans fit prediction for online shopping

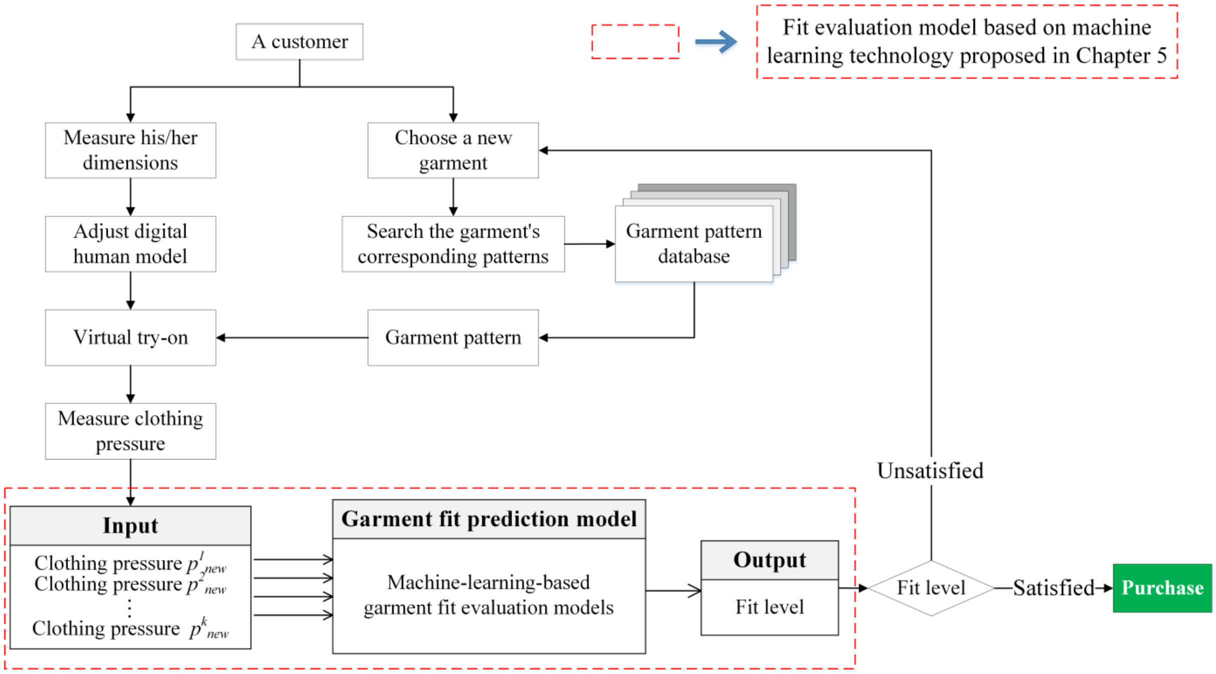


Figure 6-11 Process 4: Remote garment fit prediction for online shopping.

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 [166, 65]. The evaluation of garment fit without physical participation of customers and designers is very useful for online clothing shoppers. In this context, I introduce an application based on the

IGFEM technology proposed in Chapter 5 to estimate the fit of female jeans in an e-shopping environment (Process 4).

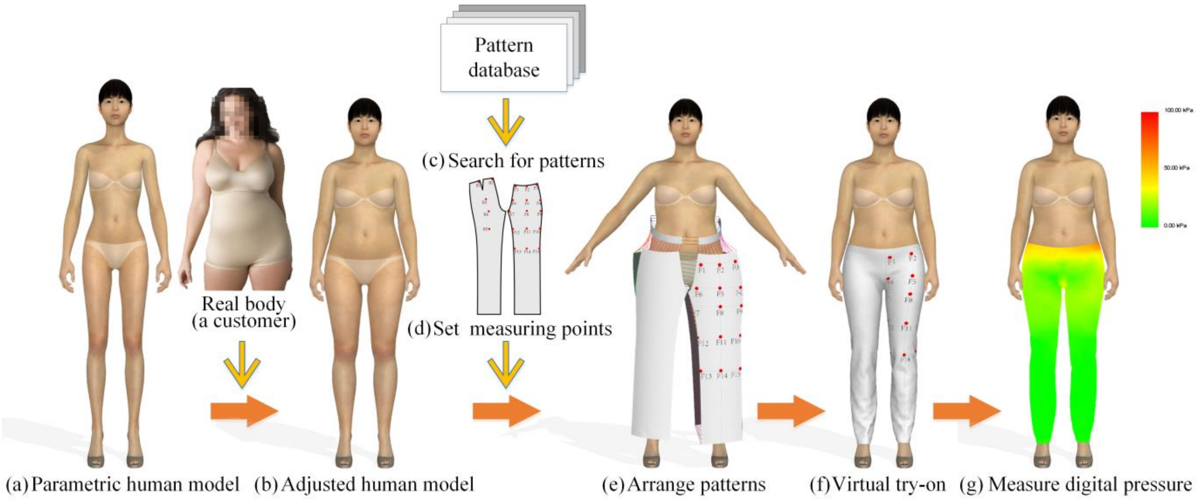


Figure 6-12 3D human model adjustment and virtual try-on.

For a specific customer, a parametric human model is used to be adapted or adjusted to the real dimensions of the concerned human body (Figure 6-12(a) and (b)). Next, I search for the garment patterns from the database of the company according to the previous body dimensions (Figure 6-12(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 (Figure 6-12(d)). Then, garment patterns are assembled on the adjusted digital human model (Figure 6-12(e)). Next, the assembled patterns are seamed together to form a 3D virtual garment (Figure 6-12(f)). Finally, digital clothing pressures are measured on the predefined key positions (Figure 6-12(g)).

Having performed the previous operations, the collected digital clothing pressures are introduced to the garment fit evaluation model (Figure 6-11) for predicting the garment fit automatically. If the predicted result meets the customer's requirement, I recommend the concerned customer to buy the garment. Otherwise, she will be invited to try another one with a different size or style. This procedure repeats until the satisfaction of the result (Figure 6-11).

6.6 Conclusion

In this chapter, I introduced four applications of the proposed knowledge-based garment design and fit evaluation system. These applications focus on different processes of garment design, development and sale. The previous results show that the proposed system can be integrated into different design processes and successfully applied to mass production, made-to-measure, mass customization, and garment e-shopping and remote design.

The comment point of these applications is that users of this system do not require advanced design knowledge and working experience. The essential difference between the design processes using this system and traditional fashion design methods is that the former integrates knowledge (fashion design, pattern making, fit evaluation) provided by design experts into the models, which will be used by inexperienced designers. The involved processes are then more systematic and less influenced by designer's personal quality and behavior. A traditional garment design method is more related to designers' personal experience and knowledge, which cannot be easily exploited by other people. Their design processes cannot be easily understood and spread to the general public. The above application examples indicate that, whatever users have professional design knowledge or not, they can always use the system to design new products and make concerned fit evaluations. This can effectively avoid the influence of uncertain human factors on the development of garment enterprises.

GENERAL CONCLUSION AND PROSPECT

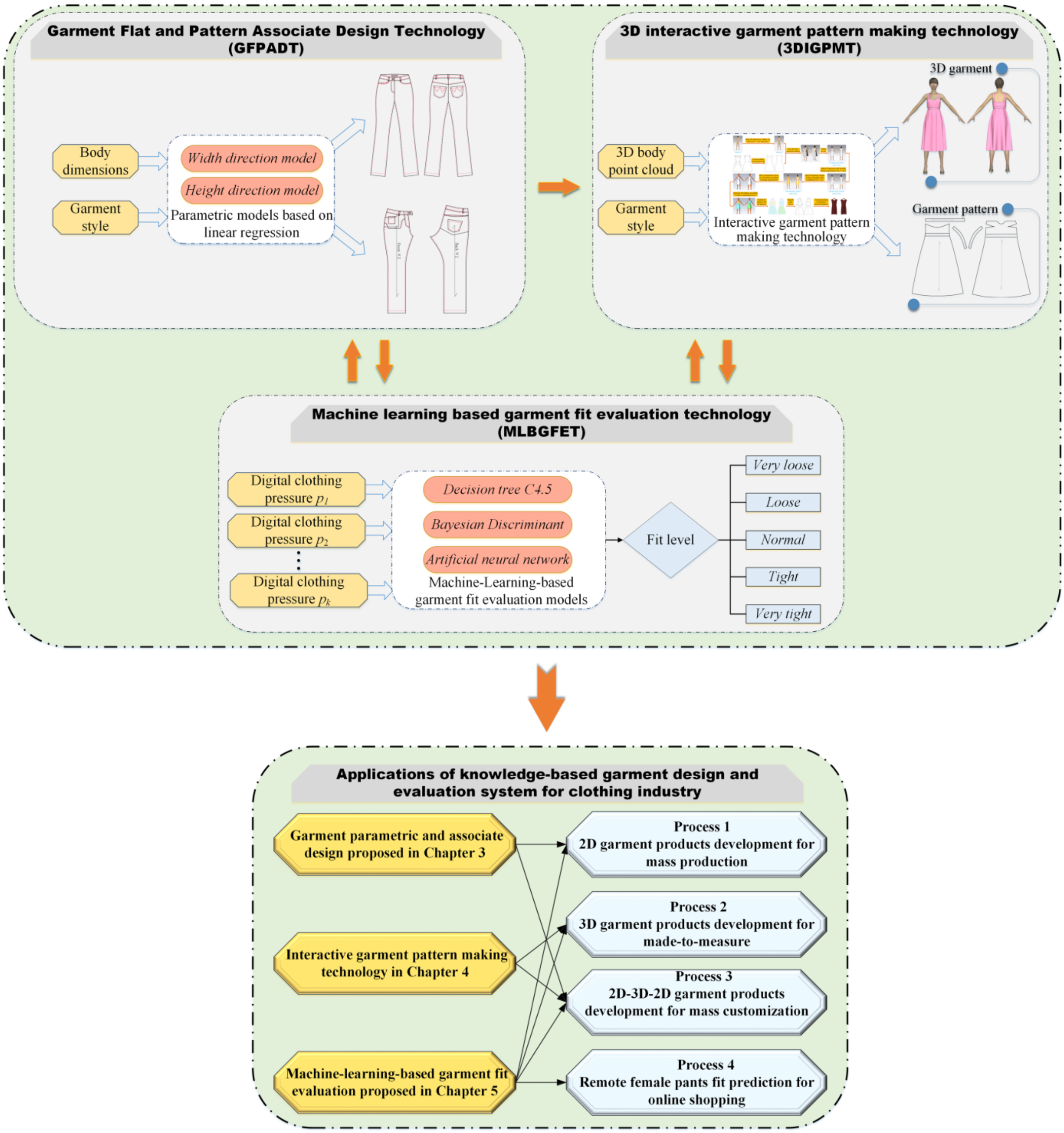


Figure 7- 1 General scheme of this thesis.

Textile/apparel industry is generally considered as a labor-intensive industry with low technological added values. However, in the situation of fierce global competitions, increasing working efficiency and reducing labor costs are the key issues to enhance the core competitiveness of textile/garment enterprises.

In this context, I wish to develop new optimized garment design processes in the classical and online virtual environments by exploiting measured data and collected professional knowledge in order to connect different design spaces and control design parameters according to the consumers' expectations on comfort and fashion. It is for this reason that I develop a knowledge-based fashion design and garment fit evaluation system in the frame of my thesis. This system is composed of the Garment Flat and Pattern Associated Design Technology (GFPADT) (Chapter 3), the 3D Interactive Pattern Making Technology (3DIPMT) (Chapter 4) and the Machine Learning-Based Garment Fit Evaluation Technology (MLBGFET) (Chapter 5). The proposed system enables to increase the quality and efficiency of design work and develop new garment products without involvement of experts. By combining the technologies of GFPADT, 3DIPMT and MLBGFET, I propose several new processes for different garment design tasks (Chapter 6). The general structure of this system is described in Figure 7- 1.

7.1 Research contributions

The main research contributions of my thesis are summarized as follows.

In the aspect of garment flat and pattern associated design:

1) Factor analysis of the anthropometric data on female lower body dimensions indicates that the height and girth factors have a contribution rate of 85.86%. The stature has strong correlations with the other dimensions in the height direction, while the waist girth and hip girth have strong correlations with the other dimensions in girth direction. Therefore, the dimensions of stature, waist girth and hip girth are selected as the key dimensions for garment pattern making.

2) Garment flats and their associated patterns have close relations. In the height direction, the dimensions of garment flats and their associated patterns can be equal. Meanwhile, in the width direction, they respect the relation of (1-0.618):1 (the golden ratio).

3) By modeling the relations between garment flats, their associated patterns and body shapes, the traditional separate works of garment flat drawing and pattern making can be connected and integrated in the same tool. According to this principle, garment flats and their associated patterns can be generated together.

4) It is feasible to integrate garment flat drawing and pattern making by GFPADT.

3D interactive pattern making:

1) Patterns can be made on a parametric 3D mannequin whose dimensions are equal to the sums of the body dimensions of the customer and the ease allowance values. This method is a feasible solution for integrating ease allowance into the process of 3D garment pattern making.

2) The outlines, which are extracted from garment flats or garment pictures, can be applied to model 3D garments. The 3D garments can meet design requirements after simple adjustments. The above method is an efficient method to model a 3D garment for 3D pattern making.

3) It is feasible to develop garment patterns by 3DIPMT.

Machine learning-based garment fit evaluation:

1) The ease allowance is not a good indicator reflecting the level of garment fit. Instead, the digital clothing pressures constitute a more relevant indicator reflecting fit levels for both tight and loose garments.

2) For obtaining acceptable prediction accuracies, the model of garment fit is based on learning from a large number of experimental data. The proposed models can predict garment fit rapidly and accurately without expert's involvement and real try-on.

3) It is feasible to evaluate garment fit by MLBGFET.

4) Compared to the prediction accuracies of the traditional garment fit evaluation methods, the proposed data learning-based models are capable of providing more accurate results. The models of Naive Bayes and decision trees are more adapted to small numbers of learning data, while the model of neural networks is more adapted to a big quantity of learning data.

7.2 Innovations in design

The innovations of my study in garment design are summarized as follows.

In the aspect of garment flat and pattern associated design:

1) Garment flat drawing and pattern making, usually belonging to different departments of one fashion company, are integrated together. Thus, garment flats and their associated patterns can be generated automatically and simultaneously.

2) By modeling the knowledge of garment flat drawing and pattern making, users without expert knowledge can also develop satisfactory garment products.

3) Constructing a bridge between artistic design (flat drawing) and engineering design (pattern making).

3D interactive pattern making:

1) Through human-computer interactions, 3DIGPMT using the principle of "what you see is what you get" enables to develop garment patterns without special knowledge.

2) 3DIGPMT can be adapted to pattern making for both tight and loose garments.

3) 3DIGPMT can develop form-fitting garment for different body shapes without making real prototypes repeatedly.

Machine learning-based garment fit evaluation:

1) MLBGFET evaluates garment fit rapidly and automatically according to the digital clothing pressures without real try-on.

2) The prediction accuracy of MLBGFET can be continuously increased along with improvement of the quality of quantity of learning data.

7.3 Research prospect

Due to the limitation of time and research conditions, it is necessary to carry out further studies in the following aspects in order to improve the current results.

In the aspect of garment flat and pattern associated design:

1) It is easy to realize the associated design of garment flats and patterns if styles are simple. However, it is difficult to handle the design rules if the styles become more complex. Therefore, in the further research, I can focus on how to apply the proposed method to deal with the complexity related to style variation.

2) In this research, the linear regression is used to model the relations between garment flats, their associated patterns and body shapes. However, these relations are not entirely linear. Therefore, the further research can be carried out by applying nonlinear models, such as neural networks.

3) In this research, the anthropometric data is collected from the Northeast Region of China. In practice, the body dimensions of different ethnic groups and different regions are quite different. A number of parametric models can be built for different customer groups in order to develop a more generic method.

In the aspect of 3D interactive garment pattern making:

1) The involved interactive clothing pattern making technology is only suitable for garments with collarless or standing collar types. In the further research, I can study how to apply this technology to other types of garments, such as closure collar and shawl collar.

2) The involved interactive clothing pattern making technology is only suitable for single-layer garments. Further study can be carried out on how to apply this technology to multi-layer garments.

3) The mentioned applications of 3DIGPMT concern human clothing only. In fact, this method can also be applied to the development of pet clothing, cartoon clothing, etc. The future in-depth study can be carried out in this area.

<u>In the aspect of machine learning–based garment fit evaluation:</u>

1) The digital clothing pressures are 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 the further research, ease allowance and clothing pressure can be combined together for evaluating garment fit in a complementary way.

2) 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. I need to apply time series analysis to study these clothing pressures and form new input variables of the fit evaluation model.

3) The application only deals with fit levels of a whole garment. However, in a more realistic situation, the fit levels at some positions of the evaluated garment could be different from those at the other positions. For example, for a specific wearer, it is possible that the waist is fit but the hip unfit. Therefore, the fit level of a garment should be first studied at different local positions then properly aggregated together to form a relevant overall fit level.

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APPENDIX

Appendix 1: Anthropometric data (unit: cm)

No.	h	LL_h	WH_h	HH_h	AH_h	KH_h	H_h	W_h	CD_h	CW_h	A_h	T_h	K_h
1	168.9	72.9	105.0	87.2	99.2	46.6	100.3	68.3	32.2	20.3	83.7	56.5	37.4
2	167.4	74.1	104.5	87.5	96.5	44.7	98.8	67.0	30.5	19.5	84.5	57.5	39.4
3	161.9	69.8	99.5	80.9	93.4	44.5	94.3	64.5	29.7	19.8	77.8	53.0	36.2
4	167.4	76.0	105.2	88.6	98.2	46.4	100.8	71.1	29.3	20.1	85.3	58.9	40.8
5	168.9	70.5	105.5	85.8	97.8	44.3	101.8	73.0	35.1	20.2	79.4	59.0	38.5
6	166.6	72.9	106.7	87.6	100.1	46.6	92.9	64.5	33.8	19.6	79.1	51.8	38.6
7	171.4	75.2	107.9	90.1	100.9	47.2	101.1	72.7	32.8	21.6	84.9	60.8	39.9
8	159.5	68.5	101.0	83.7	93.2	42.1	91.8	63.5	32.5	18.9	75.8	50.5	36.7
9	160.1	70.8	100.6	82.8	93.6	42.8	88.9	61.1	29.9	19.0	75.0	49.1	36.2
10	169.9	74.7	108.4	90.3	100.8	45.3	95.8	68.0	33.8	20.7	80.4	53.2	36.2
11	162.0	72.2	100.5	84.6	93.5	43.3	93.7	66.1	28.3	20.0	80.8	52.3	37.3
12	160.1	70.5	99.2	82.1	93.4	42.2	89.3	62.0	28.8	19.1	71.6	50.8	36.9
13	173.2	80.7	110.4	91.7	103.4	47.8	92.6	65.5	29.7	18.6	79.8	53.0	35.7
14	169.9	75.4	106.1	87.6	98.2	47.0	95.5	68.7	30.7	20.7	80.8	57.2	37.6
15	166.6	72.0	105.7	87.5	99.9	45.7	96.5	69.9	33.8	19.5	83.4	54.8	38.4
16	171.3	77.7	108.6	88.8	101.6	46.6	90.1	64.0	31.0	19.0	75.5	46.6	35.0
17	154.5	67.2	97.3	79.6	89.4	41.0	96.2	70.2	30.1	21.8	80.9	52.7	38.1
18	158.7	70.7	97.9	80.7	91.5	41.6	94.0	68.1	27.3	20.0	79.5	56.2	37.0
19	161.9	72.4	98.3	82.8	91.3	43.3	94.1	68.2	25.9	20.3	78.1	52.3	37.0
20	168.9	73.3	107.6	87.2	101.1	45.1	95.0	69.2	34.3	18.9	81.7	53.8	38.4
21	160.9	69.1	102.9	85.6	97.4	42.1	89.0	63.2	33.8	18.2	73.9	50.7	34.9
22	173.2	76.5	108.7	89.9	101.7	46.7	97.2	71.5	32.2	19.4	86.0	57.5	40.9
23	156.9	67.3	98.1	80.1	91.1	41.7	93.2	67.5	30.9	20.0	76.1	53.4	36.9
24	168.1	75.1	104.4	86.3	98.9	45.8	86.0	60.4	29.3	17.8	73.3	47.9	34.9
25	160.9	69.4	99.5	81.1	92.5	44.2	93.5	67.9	30.2	18.9	78.9	53.2	39.4
26	160.1	70.6	100.6	82.1	95.5	44.6	90.0	64.6	30.1	19.6	75.1	51.8	40.3
27	164.2	74.0	102.6	86.7	95.6	45.8	91.9	66.8	28.6	19.6	77.4	55.0	38.7
28	154.8	71.1	95.0	77.2	89.2	41.1	83.4	58.3	23.9	18.3	68.2	43.4	33.0
29	157.9	68.0	98.5	78.3	92.4	42.0	96.5	71.5	30.5	19.8	84.4	56.3	38.0
30	165.9	75.3	103.4	84.6	97.2	45.3	96.7	71.8	28.1	21.0	81.6	56.6	38.4

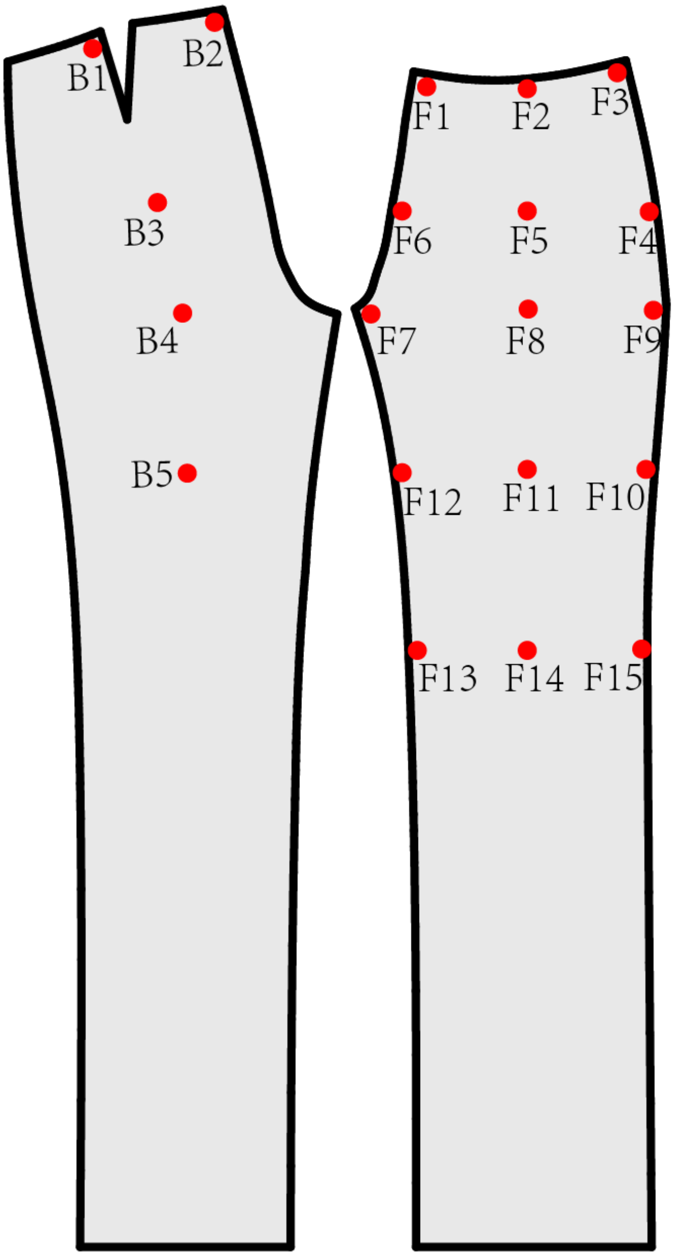
No.	h	IL_h	WH_h	HH_h	AH_h	KH_h	H_h	W_h	CD_h	CW_h	A_h	T_h	K_h
31	156.9	70.2	99.1	81.3	93.2	42.3	85.2	60.4	29.0	18.2	70.6	48.3	34.1
32	161.7	69.6	99.6	83.5	94.5	43.7	93.7	68.9	30.1	20.4	79.2	53.9	37.4
33	167.4	73.4	103.2	84.7	97.8	45.9	88.4	63.8	29.8	17.9	76.4	49.4	34.8
34	164.2	70.3	103.2	82.5	94.3	44.8	99.3	74.7	32.9	20.9	85.8	57.9	41.5
35	159.5	70.4	99.1	78.6	91.4	42.1	90.3	65.7	28.8	18.7	75.1	50.8	36.6
36	156.3	68.8	96.5	79.2	88.1	40.8	86.5	62.1	27.7	18.3	71.2	49.1	35.6
37	164.9	74.9	102.1	84.1	94.1	43.4	93.8	69.4	27.2	20.1	81.8	53.3	35.2
38	160.9	72.1	100.3	79.8	91.4	43.2	92.1	67.8	28.2	19.4	79.1	52.9	35.7
39	165.9	74.0	102.1	83.5	97.5	44.2	89.0	64.7	28.1	19.7	74.0	51.5	41.1
40	165.9	71.5	103.9	84.1	97.8	45.1	95.7	71.5	32.5	21.1	82.9	52.5	38.1
41	159.4	69.9	99.2	81.2	94.8	42.6	93.8	69.7	29.4	20.1	78.7	51.8	38.2
42	161.9	70.7	102.3	83.1	98.1	42.9	96.2	72.2	31.7	20.5	87.1	58.4	43.9
43	155.4	66.7	96.4	76.1	90.4	41.3	93.8	69.8	29.7	20.1	83.3	52.6	35.5
44	166.0	73.2	105.7	86.8	99.6	44.5	92.1	68.1	32.6	20.2	78.8	52.5	37.1
45	167.4	74.3	106.6	85.9	98.1	44.1	94.4	70.5	32.4	19.0	80.3	53.4	38.3
46	161.7	69.7	101.8	81.1	92.1	42.1	90.7	66.8	32.1	19.2	77.0	51.9	36.2
47	162.8	72.4	103.4	85.5	94.1	44.6	91.1	67.2	31.1	20.1	79.3	51.6	38.8
48	159.5	68.2	99.6	81.5	91.2	43.1	96.0	72.3	31.4	20.1	81.9	57.5	36.6
49	172.1	77.6	107.8	88.1	99.4	47.3	96.2	72.6	30.3	21.0	87.3	53.9	37.1
50	165.9	75.6	106.2	87.2	99.2	46.1	90.7	67.1	30.7	19.0	78.5	51.5	39.5
51	156.1	72.6	97.2	81.2	92.4	41.3	82.9	59.3	24.7	19.4	68.3	45.5	32.2
52	158.7	71.0	98.7	80.3	90.1	42.0	96.0	72.4	27.8	20.5	81.7	56.7	37.2
53	158.7	67.6	99.7	81.9	93.5	43.3	99.2	75.7	32.1	21.0	84.6	58.6	39.3
54	161.9	72.6	99.3	80.3	93.8	42.6	87.7	64.2	26.7	18.9	73.4	48.9	34.6
55	172.1	79.7	110.2	90.9	102.1	47.6	98.6	75.2	30.5	22.1	84.6	59.6	40.8
56	164.9	72.8	103.5	84.6	94.5	45.8	92.1	68.7	30.8	20.0	79.2	55.3	36.5
57	158.0	68.8	98.7	80.8	92.8	41.9	91.9	68.6	30.0	20.6	79.8	50.9	35.0
58	169.1	79.6	107.8	89.0	101.1	46.9	95.6	72.3	28.3	21.7	81.1	54.7	39.6
59	162.8	75.5	100.7	82.1	94.7	43.4	96.2	73.0	25.3	20.7	83.0	54.4	36.4
60	160.9	71.0	103.1	83.6	98.4	43.0	90.7	67.5	32.1	18.5	78.6	50.3	35.3
61	159.4	69.9	100.5	80.1	92.1	42.3	89.8	66.6	30.7	19.2	74.2	49.9	37.8
62	158.8	71.5	100.7	79.6	93.5	41.4	84.7	61.5	29.3	18.4	71.2	48.4	35.0
63	160.1	73.4	98.4	80.5	90.1	41.5	84.2	61.2	25.0	18.3	70.8	49.4	34.9
64	170.7	76.9	105.9	87.5	97.1	47.6	100.2	77.3	29.1	21.2	91.1	59.1	41.0

No.	h	IL_h	WH_h	HH_h	AH_h	KH_h	H_h	W_h	CD_h	CW_h	A_h	T_h	K_h
65	164.9	70.3	104.6	86.3	95.9	42.6	99.3	76.4	34.4	21.2	88.0	58.2	38.9
66	151.5	64.8	93.4	76.4	86.9	39.7	81.6	58.8	28.6	17.9	66.9	45.6	33.3
67	161.7	72.4	100.5	82.1	92.1	45.4	87.8	65.1	28.2	18.9	75.4	50.1	37.0
68	164.1	74.0	99.7	81.5	90.6	44.9	86.4	63.7	25.8	18.4	73.9	48.4	37.6
69	157.7	69.1	97.8	78.3	90.4	41.3	97.8	75.3	28.7	20.4	85.7	56.6	40.1
70	158.7	66.3	98.9	82.8	89.7	41.7	89.8	67.3	32.6	19.4	76.3	51.7	38.3
71	156.2	70.7	96.7	79.1	88.4	41.2	87.0	64.6	26.0	19.3	71.7	49.4	35.3
72	157.9	70.5	98.7	80.3	91.4	43.3	90.1	67.9	28.2	19.4	76.0	51.2	37.6
73	168.9	76.9	109.5	90.1	102.9	45.5	93.7	71.6	32.7	19.0	82.7	55.1	39.4
74	156.3	65.4	96.6	77.5	88.7	41.0	95.6	73.7	31.2	20.0	81.4	50.2	39.7
75	156.9	70.9	96.2	77.7	88.1	42.4	91.6	69.7	25.3	19.6	79.2	54.8	37.8
76	159.4	73.0	98.1	81.6	90.1	42.0	85.1	63.3	25.2	18.6	74.4	49.1	34.3
77	160.1	67.9	98.5	79.5	89.5	43.5	97.8	76.1	30.6	21.1	85.7	58.9	40.3
78	164.1	71.2	104.1	85.3	95.4	45.1	90.3	68.7	33.0	19.3	77.2	54.3	36.7
79	162.6	71.2	99.3	81.2	91.4	43.6	101.7	80.2	28.2	22.2	91.2	60.4	38.6
80	154.8	70.5	96.6	77.9	91.1	40.8	88.6	67.1	26.2	18.4	74.9	53.4	35.9
81	162.0	73.3	102.2	85.4	96.7	41.8	93.0	71.6	29.0	20.5	82.4	52.6	37.4
82	162.0	73.0	104.0	82.1	98.8	44.8	94.1	72.8	31.0	20.1	82.5	53.7	40.3
83	158.7	72.2	99.3	81.4	94.2	41.3	92.3	71.0	27.1	20.0	77.9	51.5	37.0
84	152.3	66.4	94.5	78.2	86.4	40.0	87.3	66.2	28.2	19.8	73.7	49.9	34.7
85	157.9	69.3	99.9	79.4	91.4	42.9	95.5	74.5	30.6	19.9	86.2	57.6	41.5
86	153.9	67.6	95.9	78.5	87.5	40.3	90.4	69.4	28.4	19.8	77.5	54.8	35.7
87	161.9	74.0	99.2	84.8	93.6	42.0	91.9	71.3	25.2	20.1	80.0	52.5	38.0
88	173.1	78.1	110.1	91.0	103.5	47.9	93.7	73.2	32.1	19.5	81.5	52.8	39.7
89	160.2	70.1	102.4	85.8	95.4	42.5	98.5	78.4	32.4	21.8	88.6	58.6	38.0
90	163.4	75.0	104.5	82.7	99.8	44.4	95.0	75.0	29.6	20.7	84.3	54.1	36.9
91	152.3	64.8	93.7	75.2	87.1	39.9	93.5	73.7	28.9	20.2	83.7	56.4	38.3
92	160.9	73.8	100.4	82.1	92.9	44.7	89.4	69.9	26.7	18.5	78.3	51.2	37.2
93	153.0	65.6	95.3	76.4	88.7	40.1	87.9	68.4	29.7	19.6	78.0	50.4	35.6
94	164.1	73.8	101.7	83.1	93.5	43.2	87.1	67.9	27.9	18.9	73.4	49.6	35.6
95	167.3	74.8	105.9	86.9	97.5	46.0	96.4	77.3	31.1	20.0	88.8	55.4	39.1
96	154.4	69.1	96.4	78.8	88.2	40.6	86.4	67.5	27.4	19.3	71.8	50.2	35.8
97	158.7	69.9	98.2	79.2	93.1	41.6	95.1	76.2	28.3	20.5	83.9	55.0	39.4
98	159.4	69.8	100.1	82.4	91.8	41.6	90.9	72.3	30.4	19.8	78.8	52.3	37.6

No.	h	IL_h	WH_h	HH_h	AH_h	KH_h	H_h	W_h	CD_h	CW_h	A_h	T_h	K_h
99	160.9	70.1	97.4	79.1	88.4	42.2	90.9	72.6	27.4	18.7	84.4	53.2	38.9
100	162.6	72.2	101.4	83.6	93.8	43.1	86.0	68.0	29.3	19.3	72.1	48.2	34.4
101	165.9	74.1	104.0	87.7	96.1	46.5	98.8	81.3	30.0	21.6	87.2	59.8	40.8
102	155.5	69.4	94.9	77.1	87.5	42.1	87.1	69.6	25.5	19.2	79.1	50.3	34.2
103	159.4	70.4	98.5	79.7	89.9	43.8	89.9	72.8	28.2	19.5	81.3	51.7	34.9
104	157.7	71.5	99.0	81.8	91.6	42.2	84.1	67.0	27.5	18.2	75.4	47.0	34.2
105	158.0	70.0	96.5	80.5	90.4	42.5	97.4	80.6	26.5	22.0	86.3	59.6	42.1
106	156.1	68.9	95.8	79.8	89.1	41.4	85.6	69.0	26.9	19.5	75.1	50.3	36.0

(Note: h is stature; LL_h is inside length; WH_h is waist height; HH_h is hip height; AH_h is abdomen height; KH_h is knee height; H_h is hip circumference; W_h is waist circumference; CD_h is crotch depth; CW_h is crotch width; A_h is abdomen circumference; T_h is thigh circumference; K_h is knee circumference).

Appendix 2: Measuring points of digital clothing pressure.



Appendix 3: Garment fit levels and their corresponding digital clothing pressures (Unit: Kpa): Part A

No.	Fit level	$F1$	$F2$	$F3$	$F4$	$F5$	$F6$	$F7$	$F8$	$F9$	$F10$
1	Very loose	6.92	9.57	12.34	3.22	4.35	5.66	7.82	4.35	3.19	5.02
2	Very loose	6.58	8.98	14.74	3.12	6.03	6.35	7.39	5.41	2.64	5.19
3	Very loose	7.58	9.12	8.12	1.78	5.37	7.30	13.33	4.95	1.69	3.91
4	Very loose	10.62	13.12	12.80	3.02	5.95	5.23	9.76	5.39	3.68	4.15
5	Very loose	10.01	4.65	13.47	3.08	5.54	8.68	10.87	5.06	3.65	3.36
6	Very loose	9.27	11.53	12.31	3.29	6.10	7.23	7.92	5.46	2.59	5.09
7	Very loose	5.05	7.05	14.47	2.83	4.77	5.86	10.32	4.44	2.37	4.78
8	Very loose	13.31	11.80	30.57	2.43	4.23	8.86	23.15	4.37	1.24	2.64
9	Very loose	4.83	8.92	10.85	2.38	4.11	6.19	11.18	4.72	2.67	4.97
10	Loose	14.59	16.56	19.76	2.27	4.11	6.32	8.33	4.04	2.24	4.04
11	Loose	21.51	26.90	29.51	3.82	5.17	5.88	4.95	4.21	3.14	3.84
12	Loose	17.34	22.56	20.04	3.34	4.33	7.41	8.94	4.23	1.93	3.41
13	Loose	15.66	18.35	41.54	3.54	6.46	7.26	11.84	5.42	2.32	2.67
14	Loose	40.91	24.42	10.13	3.42	4.31	13.18	23.41	3.90	2.65	2.88
15	Loose	10.65	19.53	18.32	1.96	4.61	12.41	14.93	4.39	2.23	3.52
16	Loose	14.40	21.80	19.32	4.32	4.23	7.60	11.61	4.40	2.43	3.60
17	Loose	10.92	3.36	12.43	2.87	3.98	7.90	23.31	4.68	2.40	4.23
18	Loose	13.12	17.44	7.20	3.57	4.52	5.96	9.10	4.30	2.24	4.03
19	Loose	13.31	15.86	14.97	4.22	4.55	9.57	19.59	4.55	2.64	3.93
20	Loose	17.29	21.53	21.09	3.60	5.87	6.85	9.31	5.40	3.13	4.16
21	Loose	13.80	17.34	5.91	3.85	4.57	6.20	9.67	4.39	2.25	4.44
22	Loose	21.99	24.50	21.92	3.56	6.20	12.37	42.50	5.22	3.28	3.28
23	Loose	2.50	7.30	10.04	2.89	4.20	10.93	23.73	5.65	3.06	3.71
24	Loose	5.37	9.59	10.96	3.57	5.54	17.53	20.14	5.51	1.75	3.02
25	Loose	3.92	7.57	10.17	3.20	3.67	12.92	40.45	3.77	4.78	5.48
26	Normal	5.79	8.45	9.35	2.62	3.91	12.79	39.95	3.76	3.27	4.84
27	Normal	7.17	10.38	10.97	2.31	3.28	12.66	40.14	4.06	2.26	2.15
28	Normal	8.63	11.83	13.79	2.55	3.94	12.57	27.42	4.13	2.40	1.96
29	Normal	4.95	8.71	10.87	4.52	5.79	15.08	35.91	6.34	5.49	3.07
30	Normal	6.98	10.29	10.41	4.24	5.46	14.91	34.85	5.87	4.82	4.01

No.	Normal	$F1$	$F2$	$F3$	$F4$	$F5$	$F6$	$F7$	$F8$	$F9$	$F10$
31	Normal	5.81	9.42	9.20	5.07	5.54	14.67	39.77	7.76	6.33	4.85
32	Normal	5.44	8.69	10.49	5.08	6.71	15.02	41.87	7.61	6.72	6.71
33	Normal	6.56	9.88	11.57	4.96	5.32	15.09	39.26	6.88	6.14	7.96
34	Normal	5.87	10.42	12.42	5.70	5.97	14.78	40.93	7.77	7.02	9.08
35	Normal	6.70	10.25	10.88	6.45	6.54	14.18	45.22	8.36	8.49	13.23
36	Normal	3.75	6.49	9.91	3.58	5.13	12.65	33.69	5.78	4.43	3.64
37	Normal	4.73	7.33	11.21	3.91	5.12	14.19	38.45	6.05	4.65	2.15
38	Normal	4.95	8.07	12.46	3.86	3.40	12.86	28.87	4.86	3.99	3.02
39	Normal	5.90	9.60	11.06	4.08	5.44	13.31	34.49	6.17	4.15	2.24
40	Normal	6.40	9.75	10.92	3.97	5.01	14.16	34.72	5.77	4.70	4.02
41	Normal	6.35	9.60	9.02	4.85	5.50	14.74	38.30	6.64	5.60	5.71
42	Normal	6.47	9.88	11.23	4.70	6.41	15.26	38.78	6.85	6.30	6.13
43	Normal	5.20	8.76	10.94	5.38	5.92	15.28	42.11	7.48	7.32	8.07
44	Normal	6.27	9.96	11.64	5.35	5.67	14.62	40.80	8.21	7.27	9.87
45	Normal	6.17	10.16	11.80	5.95	7.07	15.85	43.25	8.08	8.07	12.20
46	Normal	9.80	12.35	12.31	4.50	5.25	10.46	29.67	5.73	3.79	2.39
47	Normal	6.77	9.50	9.42	4.31	4.03	14.04	33.88	4.39	4.32	8.32
48	Normal	8.26	11.51	8.80	4.64	18.96	12.05	27.96	4.67	4.06	6.37
49	Tight	22.64	30.24	28.56	23.87	18.55	26.68	54.67	19.41	23.36	26.88
50	Tight	25.35	29.86	24.00	17.10	15.81	21.47	77.37	16.54	15.97	19.44
51	Tight	14.86	18.78	17.68	20.35	17.73	22.37	95.47	18.66	18.56	19.30
52	Tight	26.93	31.62	27.66	18.32	21.50	16.09	56.23	13.92	13.00	14.56
53	Tight	12.40	17.45	31.65	21.03	15.90	18.76	65.00	12.99	18.97	13.90
54	Tight	19.81	28.33	24.15	21.86	16.64	19.16	78.30	17.76	19.81	15.94
55	Tight	16.86	21.26	28.35	16.92	9.41	19.01	58.82	10.65	14.05	12.48
56	Tight	13.24	21.19	23.34	13.46	7.68	16.35	41.80	8.94	11.14	11.64
57	Tight	11.49	17.80	14.97	15.62	13.96	28.12	61.43	16.05	14.24	14.51
58	Tight	12.56	18.51	19.33	13.18	12.44	24.58	75.60	13.69	11.06	9.47
59	Tight	7.28	10.27	8.02	10.30	8.99	17.01	50.64	14.18	12.33	14.10
60	Tight	19.94	25.48	23.24	21.93	16.09	28.12	59.49	18.81	17.76	16.35
61	Tight	18.37	28.97	26.09	12.56	10.62	26.96	46.78	9.99	12.38	11.86
62	Tight	17.87	23.38	22.18	17.46	14.61	14.68	43.36	12.27	12.66	17.92

No.	Tight	$F1$	$F2$	$F3$	$F4$	$F5$	$F6$	$F7$	$F8$	$F9$	$F10$
63	Tight	18.51	24.90	21.88	7.27	10.55	13.05	33.72	6.53	4.78	5.58
64	Tight	17.20	22.37	17.92	8.57	8.35	9.40	40.06	5.00	5.59	6.86
65	Very tight	64.00	72.19	60.45	48.51	44.23	41.37	56.77	41.65	40.08	42.95
66	Very tight	54.08	64.12	50.51	37.64	39.71	29.37	60.72	34.12	35.95	41.69
67	Very tight	56.25	65.31	51.44	39.63	37.43	35.65	60.45	33.98	32.71	28.63
68	Very tight	40.92	48.56	49.82	28.59	30.13	26.97	67.30	22.98	22.25	20.57
69	Very tight	30.20	41.77	38.08	17.21	16.19	25.70	53.47	13.31	12.33	11.86
70	Very tight	29.53	41.24	38.68	24.26	16.76	17.01	67.66	23.35	20.12	19.57
71	Very tight	25.04	27.31	16.54	17.42	16.49	20.14	83.93	16.06	15.40	15.59
72	Very tight	30.81	36.80	36.99	20.15	25.20	18.77	58.13	15.70	16.54	17.48

Appendix 4: Garment fit levels and their corresponding digital clothing pressures (Unit: Kpa): Part B

No.	Fitness	*F11*	*F12*	*F13*	*F14*	*F15*	*B1*	*B2*	*B3*	*B4*	*B5*
1	Very loose	2.84	5.37	4.19	1.75	5.40	25.43	16.65	5.13	3.43	1.67
2	Very loose	3.39	5.32	4.14	1.91	5.22	28.25	17.67	4.19	2.67	1.15
3	Very loose	3.29	6.18	5.14	2.02	3.89	15.92	12.80	3.92	1.69	0.47
4	Very loose	3.39	5.10	4.34	2.22	4.58	15.93	14.98	4.24	2.36	1.15
5	Very loose	3.18	6.30	5.25	1.46	4.46	5.54	17.95	2.39	0.47	0.33
6	Very loose	3.77	5.43	4.59	2.16	4.59	23.39	20.74	3.14	1.75	0.21
7	Very loose	3.07	5.52	4.40	1.84	4.95	22.71	16.27	4.81	2.31	0.94
8	Very loose	3.56	4.69	2.34	2.00	2.40	35.11	12.51	1.75	1.26	0.50
9	Very loose	2.93	5.19	4.49	1.85	5.22	24.18	14.32	4.78	2.67	1.02
10	Loose	2.78	6.10	1.95	1.74	4.38	9.37	26.35	3.97	2.06	0.58
11	Loose	2.82	5.64	1.86	1.66	4.23	34.33	29.89	4.00	2.63	1.16
12	Loose	3.06	3.14	1.83	1.85	3.27	43.30	36.70	1.72	0.59	0.15
13	Loose	3.85	3.37	2.06	2.09	3.50	44.20	40.01	2.20	0.64	0.35
14	Loose	2.80	6.27	5.11	1.55	3.42	4.31	33.04	2.90	1.78	0.47
15	Loose	3.03	6.59	2.31	1.87	3.21	8.29	25.36	1.12	0.80	0.16
16	Loose	2.76	3.26	2.16	1.51	4.32	12.92	18.48	1.67	1.74	0.45
17	Loose	3.64	6.06	4.58	6.06	3.89	18.01	24.30	2.57	2.44	0.23
18	Loose	2.61	6.39	2.15	1.41	4.21	29.10	28.20	4.00	1.51	0.27
19	Loose	2.82	6.44	1.73	2.03	3.60	35.78	28.32	2.35	1.67	0.32
20	Loose	4.05	5.93	4.53	2.33	4.48	24.74	33.74	2.36	1.33	0.19
21	Loose	3.00	5.82	1.61	1.65	4.56	13.59	28.78	4.58	1.88	0.79
22	Loose	3.24	6.72	5.19	1.86	3.05	18.85	20.61	1.70	1.97	0.39
23	Loose	2.63	6.88	5.50	1.37	4.14	17.06	16.43	2.29	0.78	0.22
24	Loose	3.37	6.80	5.31	1.74	3.81	14.38	18.04	4.01	0.42	0.37
25	Loose	5.02	4.55	4.78	2.11	1.28	11.66	11.85	5.81	5.79	5.89
26	Normal	3.91	4.81	5.00	2.61	2.44	8.81	10.45	4.11	3.21	5.81
27	Normal	3.63	6.88	2.35	1.99	1.81	12.01	12.34	5.08	2.59	1.32
28	Normal	3.88	6.87	2.50	1.83	2.59	13.89	14.02	5.95	1.06	1.04
29	Normal	3.72	6.37	4.83	2.14	2.91	8.96	13.86	6.86	3.11	3.01

No.	Normal	$F11$	$F12$	$F13$	$F14$	$F15$	$B1$	$B2$	$B3$	$B4$	$B5$
30	Normal	4.53	5.78	5.22	2.23	2.33	12.43	13.72	6.89	3.60	5.58
31	Normal	5.29	5.60	5.52	2.06	1.74	13.42	15.27	8.26	4.98	7.27
32	Normal	6.30	5.51	5.78	2.26	1.09	14.04	15.26	8.00	5.08	7.62
33	Normal	6.23	6.07	6.09	1.78	0.84	13.52	14.14	8.93	4.10	9.71
34	Normal	9.54	7.78	6.28	2.80	0.89	14.17	14.31	9.13	5.38	11.59
35	Normal	14.29	12.14	7.68	6.73	4.01	13.12	13.24	9.96	6.92	13.71
36	Normal	3.86	7.86	5.62	1.92	2.31	14.61	16.64	14.75	3.15	2.72
37	Normal	2.59	7.71	2.70	1.67	2.09	14.68	16.60	6.20	3.31	1.00
38	Normal	2.32	7.64	2.97	1.52	3.39	14.63	16.51	7.33	2.09	0.88
39	Normal	3.90	6.31	4.74	2.19	1.86	12.00	13.44	6.21	2.11	3.17
40	Normal	4.22	5.90	5.22	2.42	2.50	12.83	13.36	7.16	3.63	5.28
41	Normal	5.96	5.56	5.52	1.96	1.28	13.74	14.74	8.61	4.43	6.79
42	Normal	6.56	5.62	5.99	2.21	1.21	13.32	14.27	8.22	4.27	8.49
43	Normal	7.21	6.23	6.25	2.81	0.61	13.50	14.35	9.40	5.59	9.35
44	Normal	8.17	7.45	6.90	2.76	0.78	13.45	14.10	9.50	6.41	10.50
45	Normal	12.45	11.91	7.38	6.00	3.39	13.98	14.19	9.99	7.44	14.16
46	Normal	4.21	6.89	5.41	2.48	2.39	15.82	16.42	7.93	0.28	3.21
47	Normal	6.71	5.85	6.34	2.30	0.97	10.55	11.21	6.85	5.49	8.29
48	Normal	5.07	7.12	6.28	2.04	0.74	12.17	13.54	7.49	5.81	7.43
49	Tight	22.01	24.12	11.54	12.27	16.21	47.76	67.26	27.44	18.66	29.31
50	Tight	17.23	18.55	6.06	4.25	3.61	55.81	64.24	21.76	14.14	24.31
51	Tight	20.59	28.65	7.32	8.50	8.38	32.55	50.28	17.80	15.18	23.64
52	Tight	11.91	12.18	5.76	3.03	3.82	34.59	43.32	18.35	7.91	14.09
53	Tight	14.27	13.06	5.10	2.27	2.50	43.60	48.87	17.42	14.72	9.32
54	Tight	18.97	15.98	5.35	3.38	4.02	54.06	44.62	20.70	13.42	16.21
55	Tight	13.03	13.85	3.33	2.85	3.04	24.12	60.27	15.65	10.01	14.64
56	Tight	10.55	14.19	3.88	3.07	2.85	49.26	62.84	19.28	8.37	15.35
57	Tight	17.56	26.10	6.47	4.41	5.34	27.70	33.14	15.06	10.45	18.96
58	Tight	12.25	11.86	2.64	2.76	2.18	61.89	46.02	15.94	12.53	14.48
59	Tight	15.72	12.75	6.16	2.28	4.19	28.90	32.81	12.29	8.33	13.83
60	Tight	17.11	17.21	6.03	3.14	4.78	32.43	40.83	20.62	13.20	15.55
61	Tight	10.33	8.75	2.37	2.78	3.93	49.77	29.13	13.70	10.67	10.62

No.	Tight	$F11$	$F12$	$F13$	$F14$	$F15$	$B1$	$B2$	$B3$	$B4$	$B5$
62	Tight	15.37	17.23	5.34	5.02	3.75	37.07	59.08	19.71	11.43	21.74
63	Tight	4.91	7.67	7.19	2.35	1.90	66.05	56.96	8.55	5.14	7.28
64	Tight	5.43	6.84	7.52	2.33	2.32	40.66	29.33	7.87	6.58	12.74
65	Very tight	39.46	38.27	25.94	24.83	28.84	70.46	79.93	42.97	30.25	41.47
66	Very tight	39.35	41.77	30.28	31.33	30.40	62.64	80.69	45.24	30.71	45.41
67	Very tight	27.29	29.35	9.73	7.54	6.23	96.70	82.96	43.91	33.00	32.12
68	Very tight	18.09	16.45	6.26	2.51	3.74	70.15	52.24	29.78	18.67	21.47
69	Very tight	13.72	13.35	3.07	2.65	3.53	53.40	46.08	20.04	15.15	13.24
70	Very tight	20.99	17.11	7.67	4.55	4.07	23.47	29.56	10.40	8.07	15.56
71	Very tight	15.09	17.16	2.98	3.03	2.48	38.16	51.16	18.39	13.61	18.20
72	Very tight	13.03	12.54	6.10	2.65	3.99	53.92	42.91	21.92	10.33	15.13

Appendix 5: Published and submitted papers

1. **Kaixuan Liu**, Jianping Wang, Xianyi Zeng, Xuyuan Tao, Pascal Bruniaux and Edwin Kamalhac, *Fuzzy classification of young women's lower body based on anthropometric measurement.* International Journal of Industrial Ergonomics, 2016. **55**: p. 60-68 DOI: http://dx.doi.org/10.1016/j.ergon.2016.07.008.
2. **Kaixuan Liu**, Jianping Wang, Xianyi Zeng, Xuyuan Tao, and Pascal Bruniaux, *Using artificial intelligence to predict human body dimensions for pattern making*, in *Uncertainty Modelling in Knowledge Engineering and Decision Making*. 2016, World Scientific. p. 996-1001 DOI: http://dx.doi.org/10.1142/9789813146976_0154.
3. **Kaixuan Liu**, Jianping Wang, Xianyi Zeng, Xuyuan Tao, and Pascal Bruniaux, *Garment fit evaluation based on bayesian discriminant*, in *Uncertainty Modelling in Knowledge Engineering and Decision Making*. 2016, World Scientific. p. 990-995 DOI: http://dx.doi.org/10.1142/9789813146976_0153.
4. **Kaixuan Liu**, Edwin Kamalha, Jianping Wang, and Tarun-Kumar Agrawal, *Optimization Design of Cycling Clothes' Patterns Based on Digital Clothing Pressures.* Fibers and Polymers, 2016. **17**(9): p. 1522-1529 DOI: http://dx.doi.org/10.1007/s12221-016-6402-2.
5. **Kaixuan Liu**, Jianping Wang, Chun Zhu, and Yan Hong, *Development of upper cycling clothes using 3D-to-2D flattening technology and evaluation of dynamic wear comfort from the aspect of clothing pressure.* International Journal Of Clothing Science And Technology, 2016. **28**(6): p. 736-749 DOI: http://dx.doi.org/10.1108/IJCST-02-2016-0016.
6. **Kaixuan Liu**, Edwin Kamalha, Jianping Wang, and Tarun-Kumar Agrawal, *Wear comfort analysis from aspect of numerical garment pressure using 3D virtual-reality and data mining technology.* International Journal Of Clothing Science And Technology, 2017, (Accepted).
7. **Kaixuan Liu**, Jianping Wang, Xianyi Zeng, Xuyuan Tao, Pascal Bruniaux and Edwin Kamalhac, *Fit evaluation of virtual garment try-on by learning from digital pressure data.* Knowledge-Based Systems, (Major revision).
8. **Kaixuan Liu**, Jianping Wang, and Edwin Kamalhac, *Construction of a body dimensions' prediction model for garment pattern making based on anthropometric data learning.* The Journal of the Textile Institute, (Major revision).

9. **Kaixuan Liu** and Edwin Kamalhac, *A mixed human body modeling method based on 3D body scanning for clothing industry*. International Journal Of Clothing Science And Technology, (Minor revision).

10. **Kaixuan Liu**, Jianping Wang, Xianyi Zeng, Xuyuan Tao, and Pascal Bruniaux, *Parametric design of garment flat based on body dimension*. International Journal of Industrial Ergonomics, (Under review).

11. **Kaixuan Liu**, Jianping Wang, Xianyi Zeng, Xuyuan Tao, and Pascal Bruniaux, *Interactive garment pattern making technology*. Computer-Aided Design, (Under review).

12. **Kaixuan Liu**, Jianping Wang, Xianyi Zeng, Xuyuan Tao, and Pascal Bruniaux, *Associate design of garment flat and pattern*. Computers in Industry, (Submitted).

13. Yan Hong, Xianyi Zeng, Pascal Bruniaux, and **Kaixuan Liu**, *Interactive virtual try-on based three-dimensional garment block design for disabled people of scoliosis type*. Textile Research Journal, 2016 DOI: http://dx.doi.org/10.1177/0040517516651105

14. Yan Hong, Xianyi Zeng, Pascal Bruniaux, **Kaixuan Liu**, and Yan Chen, *Virtual reality based collaborative design method for designing customized garment of disabled people with scoliosis*. International Journal Of Clothing Science And Technology, 2017 (Accepted).