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Min DONG

Development of an Intelligent Recommendation System to Garment Designers for Designing New Personalized Products

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Thèse co-dirigée par
MM.Xianyi ZENG *et* ***Ludovic KOEHL***

Membres du Jury

Isis TRUCK, University Paris 8	Rapporteur
Rosario TOSCANO, Ecole Nationale d'Ingénieurs de Saint-Etienne	Rapporteur
Anne-Marie JOLLY, Université Orléans	Examinateur
Xianyi Zeng, ENSAIT Roubaix	Directeur de thèse
Ludovic KOEHL, ENSAIT Roubaix	Co-Directeur de thèse

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Abstract

Today, under the fierce international competition, meeting consumers' personalized requirements with low costs has become a key concern for many garment enterprises and brands. The commercialized garment CAD systems have been widely used in apparel industry for realizing 2D and 3D virtual prototypes and virtual garment fitting on specific body shapes. However, the existing researches on garment CAD mainly focus on technological development of virtual design processes and rarely deal with traditional designers' knowledge and services of consumers and designers. In practice, fashion designers play a vital role in a successful design process. It is necessary to integrate the designers' knowledge and experience into the current garment CAD systems so as to quickly provide feasible human-centered and low-cost design schemes for each personalized demand. In the same time, data-based services, such as recommendation systems, human body shapes modelling and classification, and garment fit evaluation, should also be integrated into the garment CAD systems in order to increase the efficiency of the design process and facilitate the use of the CAD tools.

In my PhD research project, we originally propose a Designer-oriented Intelligent Recommendation System (DIRS) for supporting the design of new personalized garment products. For developing this system, we first identify the key components of a garment design process, including human body measurements, fashion theme, design style, fabric and color, and then set up a number of relevant databases. Of these key components, the last three ones are the garment design factors, from which each design scheme can be formed. Second, we acquire the anthropometric data and designer's perception on body shapes by using a 3D body scanning system and a sensory evaluation procedure. Third, an instrumental experiment is conducted for measuring the technical parameters of fabrics, and five sensory experiments are carried out in order to acquire designers' knowledge. The acquired data are used to classify body shapes and model the relations between human bodies and the design factors by using fuzzy techniques and rough sets theory. From these models, we set up an ontology-based design knowledge base, including key data and relevant design rules. This knowledge base can be updated by dynamically learning from new design cases. On this basis, we put forward the knowledge-based recommendation system. This system is used with a newly developed design process, i.e. personalized design requirements identification – design scheme recommendation – 3D virtual prototype display and evaluation – design parameters adjustment. This process can be performed repeatedly until the designer's satisfaction. The proposed recommendation system has been validated through a number of successful real design cases.

Key Words: Recommendation System; Personalized Garment Design; Sensory Evaluation; Fuzzy Techniques; Rough Sets; Ontology; Design Knowledge Base; 3D Virtual Display

Développement d'un Système de Recommandation Intelligent Orienté vers les Créateurs de Vêtements en vue de Conception de nouveaux Produits Personnalisés

Abstrait

Aujourd'hui, sous la pression de la concurrence internationale féroce, répondre aux besoins personnalisés des consommateurs, à faible coût, est devenu une préoccupation majeure pour de nombreuses entreprises de l'habillement et les marques. Les systèmes de CAO commercialisés ont été largement utilisés dans l'industrie de l'habillement pour réaliser des prototypes virtuels 2D et 3D et l'essayage virtuel de vêtements sur des morphotypes spécifiques. Cependant, les travaux existants en CAO confection se concentrent principalement sur les technologies de processus de création virtuelle et traitent rarement les connaissances et les avis et envies des consommateurs tout autant qurees réelles attentes des créateurs. Dans la pratique, les créateurs jouent un rôle essentiel dans un processus de création. Il est nécessaire d'intégrer leurs connaissances et leurs expériences dans les systèmes de CAO confection tels qu'ils existent afin de fournir rapidement, pour chaque demande personnalisée, des plans de création réalisables à coût moindre et surtout orientés vers l'humain. Dans le même temps, les services utilisant des données, tels que les systèmes de recommandation, la modélisation et la classification des morphotypes humains et l'évaluation du taillant des vêtements, doivent être également intégrés dans les systèmes de CAO confection afin d'accroître l'efficacité des processus de création et de faciliter l'utilisation des outils.

Durant mes travaux en thèse, nous avons imaginé et posé les briques d'un système de recommandation intelligent (DIRS) orienté vers les créateurs de vêtements afin de les aider à créer des nouveaux produits personnalisés. Pour développer ce système, nous avons dans un premier temps identifie les composants clés du processus de création, comprenant les mensurations de morphotypes, les thèmes liés à la mode, les styles de création, les matières et les couleurs, puis nous avons créé un ensemble de bases de données pour collecter les données pertinentes. Parmi ces données clés, les trois sont liées en propre aux facteurs de la création du vêtement. Dans un deuxième temps, nous avons acquis des données anthropométriques, recueilli la perception du concepteur à partir de ces mêmes morphotypes en utilisant un body scanner 3D et une procédure d'évaluation sensorielle. A la suite, une expérience instrumentale est conduite pour capturer les paramètres techniques des matières, nécessaires à leur représentation virtuelle en lien avec les morphotypes. Enfin, cinq expériences sensorielles sont réalisées pour capitaliser les connaissances des créateurs. Les données acquises servent à classer les morphotypes, à modéliser les relations entre morphotypes et facteurs de la création par le biais de techniques du flou et de la théorie des ensembles approximatifs. A partir de ces modèles, nous avons mis en place une base de connaissances de la création mettant en œuvre une ontologie munie des données clés et des règles de création pertinentes. Cette base de connaissances est mise à jour par un apprentissage dynamique au travers de nouveaux cas présentés en création. Ce système est utilisé au sein d'un nouveau processus de création, comprenant l'identification personnalisée des exigences liées à la création, la recommandation de plans de création, la visualisation et l'évaluation du prototype virtuel 3D ainsi que l'ajustement des paramètres de création.

Ce processus peut s'effectuer autant de fois que nécessaire jusqu'à la satisfaction du créateur. Le système de recommandation proposé a été validé à l'aide de plusieurs cas réels.

Mots clés: Système de Recommandation; Création de vêtements personnalisés; Évaluation sensorielle; Techniques du flou; Ensembles approximatifs; Ontologie; Base de connaissances de la création; Visualisation de produits virtuels 3D

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GENERAL INTRODUCTION

Today, under the competitive economic pressures in which more and more consumer's demands towards personalized products in terms of fashion and functional properties, industrial enterprises urgently need a new production and business mode, by which all activities throughout the product supply chain can be more focused on consumer's needs with low cost and quick reactivity. Mass customization is the process of providing goods or services that can be modified to satisfy a specific population's need and realizing quick personalized design with low costs. It has been regarded as a successful strategy in manufacturing and service industries in the past three decades.

In current apparel industry, garment designers are trying to design mass customized garments with the aid of two new techniques including 3D body scanning technology for obtaining anthropometric data and virtual reality technology for 3D human modeling and 3D garment design. 3D scanning technology can help to capture accurately human body dimensions and establish 3D human body models. It also delivers the output in a digital format which can be integrated automatically into apparel CAD systems. On this basis we can describe 3D features of a human body and carry out corresponding digital garment models in mass customization. This makes it possible to create garments which can be moulded to the three-dimensional shapes of specific human bodies.

However, in current mass customization systems, most of the existing work on garment CAD focuses on technological development for virtual garment assembling and fitting it to a specific human body model. Human professional knowledge on design is rarely involved in the process described above. It is well-known that garment designers play a vital role in the process of garment customization. In fact, in regular garment design, experienced designers generally master some knowledge, composed of rules, for different ranges of garments, especially for personalized design. This knowledge obtained from designer's experiences should be exploited in the future development of virtual garment prototypes. When a customer or a young designer is not sure which garment is more suitable for a specific wearer in terms of fashion styles and body shapes, the designer's knowledge can provide personalized recommendations according to consumer's needs on fabrics, styles, colors, and so on. Therefore, for the majority of consumers and young designers, the knowledge-based personalized recommendation could be more effective because it can help them to select relevant customized garment products or design solutions with experienced designer's knowledge. It is for this reason that garment recommendation systems should be well-developed, enabling to formalize and exploit professional knowledge of designers for quickly delivering small series customized garment design schemes. Fashion recommendation systems can also play a key role in e-shopping and CAD-based collaborative design for garments.

In addition, virtual reality technology plays an important role in modern mass garment customization. This technology has an impact on manufacturing industry because of the vivid 3D environment and real-time interactions supported by this technology. It provides basic technical conditions for new virtual product design and related manufacturing. In customized garment design, designers can establish virtual mannequins with complete garment sizes using virtual reality technology.

In my PhD research project, we propose a new knowledge-based designer recommendation system for designing new personalized garment products. The knowledge and experience of garment designers are fully extracted by using the techniques of sensory evaluation. Sensory evaluation is a method to evaluate objects through five human senses. In this system, sensory evaluation techniques are used to extract knowledge from design experts on relationship between body shapes and design factors (i.e. fashion theme, design style, fabric and color), and characterize human body shapes and fitting effects of new garment products. In designer's knowledge extraction, the sensory evaluation is strongly related to the socio-cultural context, fashion trends and individual aesthetic preference. Therefore, a number of emotional and hedonic descriptors have been generated by using some references describing related ambiances. For human body shape and garment fitting evaluations, we just use the regular quantitative description method for determining neutral and non-hedonic descriptors describing objects to be analyzed. In the garment design process, the proposed knowledge-based recommendation system can effectively help young designers, also general consumers, to quickly rank and select their design schemes and products that have their preference. Some simple personalized design work can be automatically realized by using this system and the successful design cases of the knowledge base. This will be significant for realizing mass customization.

In the proposed recommendation system, artificial intelligence techniques, including fuzzy techniques, rough set methods and genetic algorithms, are taken as the main tools for building the designer's knowledge base and related computational models. Especially, fuzzy techniques and rough set method play an important role in the modeling of this system since we have to deal with some uncertain and inaccuracy data. All anthropometric data and perceptual data of designers are formalized mathematically using fuzzy sets. The anthropometric data are classified by using fuzzy sets and rough sets method while the complex relations between body shapes and design factors are modeled by using fuzzy relations. The relevant weights in models are identified by analytic hierarchy process (AHP). The ultimate combination model driven by fashion themes for a specific body shape can be established according to the previous models.

Moreover, the proposed recommendation system has a feedback function. The recommended fabrics and garments as well as related fitting on the specific body shape can be displayed virtually on the 3D platform and the results can be returned to the system for automatic adjustment. The design schemes can be evaluated and adjusted repeatedly until they fulfill designers' expectations.

In this PhD thesis, the main work covers five parts as follows.

(1) To establish a representative fabrics database and design style module database on jeans.

(2) To extract adequately experience knowledge of designers on the relationship of body shapes, fashion themes, fabrics properties, patterns, and styles, and set up the corresponding models for characterizing these relations.

(3) To establish a knowledge base of garment designers on garment design.

(4) To develop a design-oriented intelligent recommendation system for aiding designers to select the most suitable design schemes (fabrics, colors, styles, …).

(5) To display virtually the recommended fabrics and garments proposed by the system and set up the expert's sensory evaluation.

The two main contributions of this PhD thesis are summarized as follows.

(1) The development of a new knowledge-based intelligent recommendation system with self-adjusting function for designing new personalized garment products by a series of interactions. Designers can quickly obtain recommendation results at any time for any new design schemes they have developed. Also, the knowledge base can become more and more

efficient by successively adding successful new design cases.

(2) A feedback function, including virtual product display and sensory evaluation as well as online product parameters adjustment, has been introduced to the proposed recommendation. The new working cycle, i.e. recommendation – 3D visualization – evaluation – adjustment, can be executed repeatedly until satisfaction of the designer in terms of personalized criteria provided by the related consumer.

This thesis is structured as follows.

State of the Art and Basic Concepts (Chapter 1)

In this chapter, we introduce the state of the art of mass customization in apparel industry, the techniques used for creating virtual human models and virtual garments, as well as the involved concepts on personalized garment design. We also analyze the existing research results on human body shape characterization and garment fitting evaluation for introducing human-centered design ideas. Besides, we present the techniques used in various existing recommendation systems, especially for garment recommendations. Finally, the basic principle and general scheme of the proposed garment design-oriented recommendation system is given.

Data Acquisition and Formalization (Chapter 2)

There are two data acquisition methods involved in this thesis for human body and garment characterization, including direct body measurements and sensory evaluation. The direct body measurements are realized on the human models, built from the anthropometric data measured from a 3D body scanner. The sensory evaluation is used for designer's professional knowledge acquisition and human body shape and garment effects characterization. For this purpose, a number of sensory experiments on human bodies and garment products have been designed. Finally, the mathematical formalization of involved data is given for further data analysis and modeling approaches.

Relevant computational and modeling tools (Chapter 3)

For formalizing and modeling the acquired data and knowledge on human bodies and garments, we first introduce several intelligent approaches (fuzzy techniques, rough sets, …) in order to model the relationship between human body shapes and design style elements. The involved concepts on fuzzy techniques include fuzzy sets, fuzzy relations, fuzzy operations and fuzzy model recognition. The involved concepts on rough sets include rough sets, Lower

Approximation and Upper Approximation, and attributes reduction in the complete or incomplete information system. Genetic Algorithm is introduced for optimizing the knowledge base during the self-adjusting procedure. Finally, the principle of how to apply these computational tools to the proposed system is described.

Modeling of human body shapes and Design Knowledge (Chapter 4)

In this chapter, we mainly discuss the mathematical models related to garment design, which constitutes the core part of the proposed system. Since garment design is human-oriented, we first analyze human bodies and set up the body shape classification model by using linear regression analysis and fuzzy techniques. In garment design, fashion themes, design styles, fabrics and colors are collectively known as design factors. Then, we set up four models characterizing relations between human bodies and the design factors by using fuzzy techniques and rough set methods according to the results of the sensory experiments. The related weights are identified by analytic hierarchy process (AHP). In each part presented previously, we provide an illustrative example. The proposed model is validated by using sensory evaluation and error analysis.

Ontology-Based Design Knowledge Base and Designer-Oriented Recommendation System (Chapter 5)

In this chapter, we first introduce the basic concepts and general principles of knowledge, knowledge base and ontology. Taking pants design as an example, we present garment ontologies including human bodies, fashion themes, design styles, fabrics and colors, and so on. Based on the knowledge models established in Chapter 4, we apply the domain-ontology method to set up the designers' knowledge base, which constitutes the basis of the proposed recommendation system. Next, we propose a feedback adjustment model based on genetic algorithm, by which we can change design rules or adjust sensory preference according to unsatisfied factors. This procedure can be repeated until the satisfaction of the designer is reached. At the end, we present two real cases for testing the proposed recommendation system.

CHAPTER 1 STATE OF THE ART AND BASIC CONCEPTS

In this chapter, we introduce the state of the art of mass customization in apparel industry, the techniques used for creating virtual human models and virtual garments, the involved concepts on personalized garment design, as well as human body shape characterization and garment fitting. Moreover, we will also analyze the existing recommendation systems, especially the ones dedicated to garments. Based on the previous concepts and techniques, we present the basic principle of the proposed fashion recommendation system developed in this thesis. This system permits to rank and select garment design schemes for young designers by exploiting design knowledge and designer's perception on body shapes and garment attributes. By using this system, garment designers can be capable of selecting appropriate fabrics and designing the most suitable fashion styles for meeting various personalized consumer's demands.

1.1 Mass Customization in apparel industry

In traditional economic model, customers usually purchase existing standard products which have been proposed by manufacturers and retailers using a massive production and sales system. However, with the development of modern society, customers become more and more demanding for purchasing personalized products that they feel the best for them. Under the new market circumstances and economic competitive pressures, enterprises urgently need a new production mode, by which all their activities throughout the supply chain can be organized around consumers' needs and profiles.

In his book *Future Shock* [1], Alvin Toffler, an American futurologist, presented an idea on new production model, which provides goods and services in order to satisfy a specific customer's need with low unit costs and short delivery time equivalent to standardized and massive production. The production mode was first named as Mass Customization (MC) by Start Davis in his book *Future Pefect* [2] and was defined by Tseng & Jiao (2001, p. 685) as "producing goods and services to meet individual customer's needs with near mass production efficiency". Mass customization is the new frontier in business for both manufacturing and service industries by providing strategic advantages and economic values. It is a marketing and manufacturing technique that combines the low unit costs of mass production processes with the flexibility of individual customization. According to M.Niblock [3], Mass Customization, enables a quick realization of diversified customized products while not introducing additional cost.

In practice, meeting specific needs of a target market is not easy because customization of products usually requires more production time and professional expertise and then it cannot be realized massively for a great number of consumers. However, the development of information technology (Internet, virtual reality, big data, data mining, …) has given mass customization more opportunities by adopting a new Internet-based business model. Under the new business model, production and design can be more flexibly organized and realized through interactions in web-based digital platforms. However, in practice, manufacturers do not wish to give up the exiting production models and completely rebuild new ones because the traditional business models with mass production still bring them important business benefits. Therefore, industrial companies have been struggling to meet customers' personalized needs while not giving up the benefits gained from mass production.

Mass customization is also called "built to order" because it allows end-users to add new functionalities or change some existing ones for a core product [4]. Under this production model, the customers need to inform the manufacturers or retailers of what kind of products they want to purchase, where they expect to purchase the product, and what price they expect to pay. However, in practice, many customers and designers do not fully know what kinds of products are more suitable for themselves. In this context, it is very meaningful if customers and their product designers can receive some advises or recommendations on products and services, automatically generated from expertise of high level according to the customer's personalized needs and preferences.

Mass customization has been regarded as a successful strategy in manufacturing and service industries for the past three decades. However, in apparel industry, it is still at the exploration stage [5]. The company of Levi Strauss is the first large apparel company that successfully offers mass customized garments to customers. Since then, other companies, like HYMON Company of Japan, Baird Menswear Company of British, Hongling Group Company of China, also launched mass customized products. In the existing solutions of apparel industry, garment mass customization is mainly realized by developing customized garment dimension and module. The concerned approaches deal with 3D body scanning technology, 3D human modeling and classification, virtual try-on with garment prototypes, and web-based visualization and evaluation of virtual garments. Some key technical details about the current garment mass customization are summarized below.

1.1.1 Anthropometric technology and 3D body scanning

Anthropometric technology aims at characterizing the features of human body shapes by using various measuring methods. Its development goes through three stages.

In the first stage, designers identify directly human bodies using the traditional hand measuring method. Early in the fifteenth century, Leonardo da Vinci was fascinated by the survey of the human body and the proposed methods were assimilated into the possibilities of today [6]. Since the late 1800s, anthropologists used tape measures and calipers for measuring human body. These methods are time-consuming, inaccurate and require to record results manually.

The second stage is a 2-dimensional measuring process by photographing. The measure speed is quick and the cost is low, but we cannot directly obtain the 3-dimensional information of human bodies by using this method. Hand measuring and statistical analysis should be used to support this method.

In practice, the main challenge in body measurements lies in obtaining the accurate surface of the human body, which is rather complex in some key positions. In this situation, 3D body scanning technologies, permitting to build a digital 3D copy of the corresponding physical surface, can be efficient for solving this problem.

Since the 1980s, the 3D body scanning technologies have grown rapidly and been widely applied in modern apparel industry [6]. They can catch the surface information of human body by using optical techniques combined with light sensitive devices (3D scanners) without contact with human bodies, and can rapidly and accurately acquire hundreds of, even thousands of reproducible measurements from the human body in dozens of seconds. Amongst so many possible applications of the 3D body scanning, the main significant ones are the use of point data cloud for generating virtual or physical clothing model, and the use of critical landmarks and anthropometric data to guide the design and sizing of garments.

A general 3D scanner is composed of one or several light sources, one or several capture devices, a computer system and a monitor displaying collected data. A typical 3D body scanning system is shown as follows.

Figure 1-1 The German VITUS Smart LC3 3D body scanning system

Source: http://www.leatech.net/

In the scanning process, the measured subject is asked to wear light-colored corsets only without shoes and any accessories, and then stand on the footprint sign of the square scanner's platform with a standard posture. This posture requires her/his eyes keep horizontal, both shoulders maintain natural, the arms bend slightly without exposing to the body and open outward, and five fingers make a fist. The standard standing posture is shown in Figure 1-2.

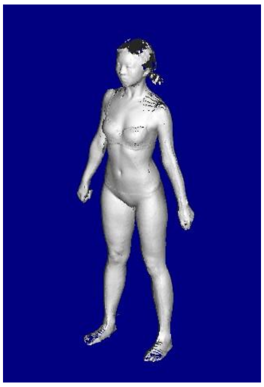


Figure 1-2 The standard standing posture during the scanning process

During the scanning process, two or four scanning units installed on the vertical towers respectively start to scan the entire body from the subject's head and move down. It generates a great number of measurements on the human body in a few seconds only. The software system of the scanner then combines the 2D models taken from the different scanning units in order to form a smooth and complete 3D model of the human body. Based on this 3D model, we can describe the 3D features of a human body and establish the corresponding digital model. The digitalized human model can be integrated automatically into a commercialized apparel CAD system, such as the products of French Lectra Company and American Gerber Company. This digitalized human model enables to create garments which can be moulded to the three-dimensional shape of a specific human body.

With the development of information technology and the improvement of garment manufacturing digitization & automation, the non-contact body scanning technology will replace the traditional measuring method and become a key technology for garment mass customization.

1.1.2 Virtual reality technology in apparel industry

Virtual Reality is the science to integrate human and information [7]. Early in 1965, in his paper *The Ultimate Display* [8], Sutherland first presented the idea about virtual reality with interactive graphic display, force feedback device and voice announce. In 1966, the research on Head Mounted Display (HMD), a hardware device for virtual reality, was developed in the American MIT Lincoln laboratory. Shortly after the first HMD prototype completed, researchers added a force feedback device that can simulate force and touch to the system. The first full functioning HMD system was born in 1970. In 1989, the concept of Virtual Reality (VR) was formally presented by Jaron Lanier, the founder of the American VPL Research company. It is defined as a computer simulation system to create and experience the virtual circumstances (i.e. Reality), which may be real simulation or imaginary.

Virtual reality technology had been widely applied in various fields and its first applications in apparel industry can be found in early 1980s. Based on traditional garment design and sample manufacturing, this technology was used to realize 3D garment design and virtual try-on by combining it with digital simulation technology. By introducing virtual reality technology, the 3D garment CAD systems have become more powerful. Currently, the most recognized systems include ModersV7 (French Lectra company), V-Sittcher (American Gerber company), CLO 3D Korean CLO company, etc. They can realize basic 3D garment design and revise, display the animation effects on garment wearing comfort, simulate the fabric draping effects and realize the 360° rotation. Using these systems, it is possible to realize garment mass customization for remote consumers [9].

In customized garment design, designers can establish virtual mannequins with specific garment sizes using virtual reality technology [9]. For example, the Japanese AGMS garment CAD software offers the possibility of adjusting the sizes of virtual mannequins according to various specifications. Now a number of garment CAD brands can provide the remote customized sizing services to their specific target customers. During a virtual try-on process, a garment prototype virtually sewed by a computer is tried on a computerized human model of the consumer. By using the virtual reality technology, the designer can view the designed 3D garments at any angle and modify them at any time until his/her full satisfaction. That will certainly accelerate design process and save design time and costs.

In a word, virtual reality technology plays an important role in modern mass garment customization and we should take its advantage to aid garment design.

1.2 Involved Concepts on Personalized Garment Design

Garment mass customization aims at developing design schemes and related garments by combining all the three design factors, i.e style, color and fabric, in order to meet consumer's personalized body shapes and fashion and functional preferences.

1.2.1 Personalized style design

Personalized style design covers two aspects. The first one is the modularized design [10]. The modularized design of a garment refers to decomposing a garment into multiple modules according to the garment structure and then selecting and deforming them based on the customers' demands or design objective until obtaining a suitable design scheme.

The modularized design of a garment is very flexible because users can obtain various garment design results by deforming and configuring different modules. New design schemes can be widely generated when adding or changing a module. It can greatly enrich the base of garment design solutions and help to meet various consumers' personalized demands. The modularized design method has a greater adaptability and can be achieved automatically by using computers. If a module is not conform to a specific demand, the designer can adjust it by using the module deformation at any time until its satisfaction is reached. Therefore, it is usually considered as an intellectualized design method, which is relevant to garment mass customization. The general principle of the modularized design is described in Figure 1-3.

In the garment modularized design, the first problem is the decomposition of modules. In practice, garment modules include fixed modules and optional modules. Fixed modules are necessary in any garment design while optional modules could exist or not. Moreover, module decomposition cannot be arbitrary but should both follow the garment structure and meet design principles.

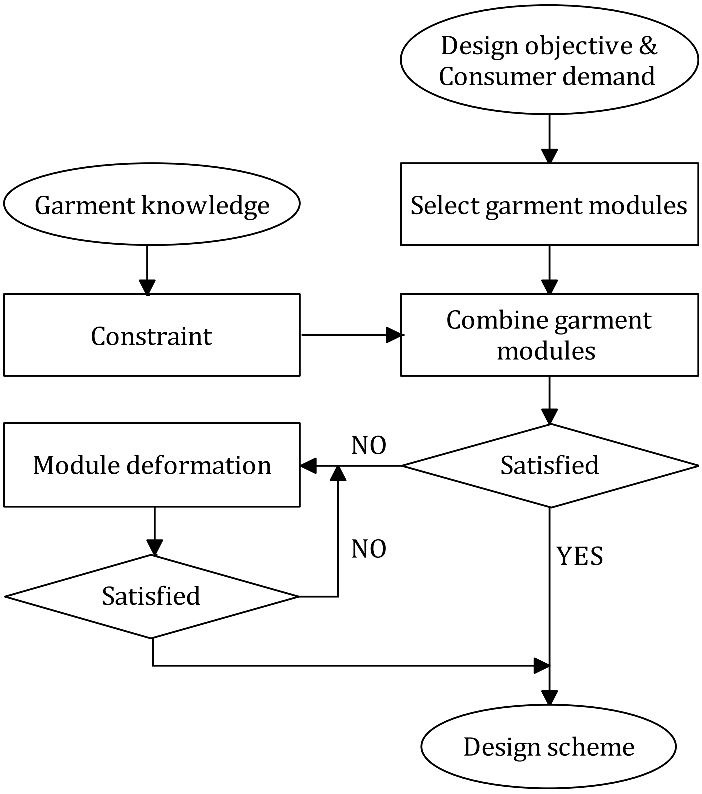


Figure 1-3 The concept diagram of modularized design

Generally, four principles need to be considered in garment modularized design.

(1) The number of modules should be moderate. The combination of a great number of modules will be very complex and the related computing workload will be heavy. On the contrary, the variety of design styles with a very few number of modules will be too small and the demands of diversity cannot be satisfied.

(2) The fixed modules should be decomposed based on the garment structure and body structure. The garment structure should be very relevant to the body structure. Therefore, the garment modules should be defined according to the different parts of the human body.

(3) The optional modules should be decomposed according to the required details and accessories.

(4) The decomposition should satisfy the demand of garment pattern making and tailoring.

The other aspect of style design is Made To Measure (MTM) for private customization. This is a unique design for specific individuals and it is mainly used in individual tailoring or advanced clothing customization but not fit for mass customization. Therefore, it is not considered in our research.

1.2.2 Selection of fabrics in personalized garment design

Fabric is one of the important factors for expressing fashion themes. During garment design, selected fabric materials should satisfy both designers' requirements and expectations in terms of appearance, fit and comfort, and garment manufacturers' technical requirements and functionally restrictions. Therefore, it is necessary to characterize fabrics in terms of physical, mechanical, aesthetic and sensory properties. The characterization of fabric properties can be realized by the objective and subjective methods. The relevant fabric properties are shown in Table 1-1.

Table 1-1 The properties of fabrics

Category	Properties
Physical	Thickness, Gram Weight (Mass per unit area), Composition, Weave
Mechanical	Bending, Tensile Strength, Tear Strength, Compression, Roughness, Friction, Abrasion, Air Permeability, Water Permeability, Heat Permeability
Visual	Thickness of Surface Texture, Draping, Glossiness, Transparency …
Tactile	Softness, Flexibility, Stiffness, Roughness, Wrinkle Resistance, Fullness, Lightness, Warmness, Elasticity …

In practice, many researches showed that there are close relation between the technical parameters and sensory properties of fabrics. For example, SHINJUNG YOO [11] studied the relationship between fabric surface characters and skin contact sensations, and further found the decisive properties related to the tactile comfort. Ramalho [12] discussed the relation of friction and tactile perception of textile fabrics. Lawrence [13] determined the sensory thresholds for a particular haptic interface using pairs of friction-reducing force controllers in order to vary levels of residual frictions. Karthikeyan [14] analyzed tactile perceptions of textile materials using artificial intelligence techniques. For optimizing 3D virtual garment design, some researchers studied the perception of virtual fabrics and their relation with the properties of real fabrics. For instance, Dennis Allerkamp [15] researched tactile perception of textiles in a virtual-reality system. Xiao Chen et al. [16] analyzed the human perception on virtual fabrics and its relation with the technical parameters of real fabrics using the fuzzy ID3 decision tree model so as to reduce the perceptual gap between virtual representation and real products.

However, the existing methods are available for complete data only, namely all the key fabric parameters should be measured correctly. Once some data are missing, the relevant relations cannot be identified correctly. However, in practice, acquiring a complete dataset requires measures on all the key fabric parameters. This is a time-consuming and expensive procedure. In this situation, we need to propose a new method capable of dealing with incomplete data for extracting more correct rules and relations of fabric properties.

1.2.3 Selection of colors in personalized garment design

Color is also an important garment design factor. It can more embody people's aesthetic demands. In garment design, designers focus on visual and psychological feeling of colors, which is caused by three basic color properties including Hue, Value and Chroma. Hue is the basic character distinguishing and naming various colors. Value property of color can describes all shades of a color from white to black. Chroma expresses vivid or pure degree of a color.

In practice, these three properties of color cannot be separated. In 1905, the American artist Munsell developed the first color order system -- *Munsell Color System*[17], in which color consciousness is described accurately. This system describes three basic properties of colors by a spheroidal space model, called *Munsell Color Solid*. Each part of this model describes one specific category of colors. This model is shown in Figure 1-4.

The spatial model like a bipyramid and the projected angle from the central axis to horizontal direction expresses Hue (H). Various central angles express 10 kinds of Hues including five dominant Hues such as Red, Yellow, Green, Blue, Purple and five medium Hues such as Yellow-Red, Green-Yellow, Blue-Green, Purple-Blue, Red-Purple. Every Hue is divided into ten grades, and the grade of every dominant Hue and every medium Hue is assigned to 5.

The central axis expresses the Value (V) of achromatic color, i.e. neutral color. From black in the bottom to white in the top, Value is divided into 11 equidistant Grayscales that feel, called as Munsell Value grades, of which 0-3 grades express low Value, 4-6 grades express middle Value, and 7-10 grades express high Value.

The horizontal distance between a specific color and central axis expresses Chroma (C), which indicates the degree of color with the same Value away neutral color. The Chroma is 0 on the central axis and the farther the distance from neutral color is, the larger Chroma is. Every color is distinguished in 2 Chroma grades intervals. The maximum Chroma values of various colors are different and there is no theoretical upper limit. Generally, Chroma can be divided into 14 color gradations, of which 1-5 grades express low Chroma, 6-9 grades middle Chroma, and 10-14 grades low Chroma. The Chroma of a few colors can reach 20 even 30, such as Chroma of fluorescent materials.

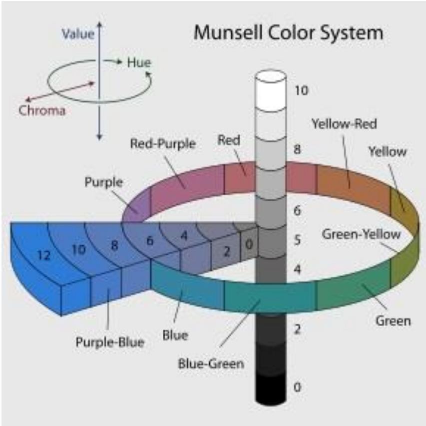


Figure 1-4 Munsell Color System

In Munsell color system, any color can be calibrated by three coordinates including Hue, Value and Chroma, and labeled as "HV/C" (Hue; Value/Chroma) in Munsell Color Cards (Figure 1-5). An example of Color Card is shown in Figure 1-6.

The color perception can be expressed by Hue, Value and Chroma while different color feeling can cause different psychological response. The main psychological feeling includes the changes in temperature, light or heavy, space and emotion, etc.

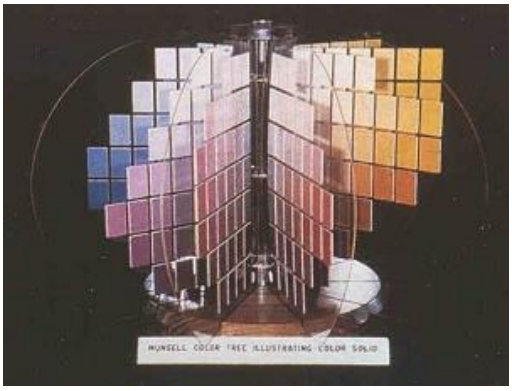


Figure 1-5 Munsell Color Cards

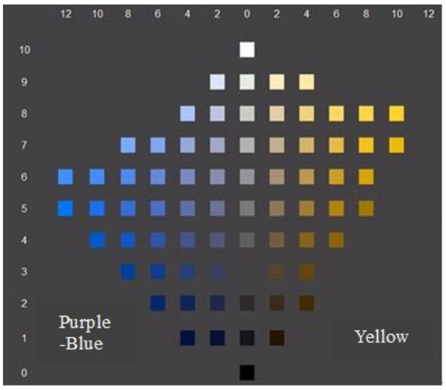


Figure 1-6 The relation of Chroma (horizontal axis) and Value (vertical between Purple-Blue and Yellow axis)

The change in temperature is mainly determined by Hue. In color psychology, red and orange are regarded as the warmest color, while blue and green as coldest color. Generally, the change in light or heavy is mainly determined by Value. The higher the Value is, the lighter the color feels; on the contrary, a lower Value leads to a heavier color feeling. The color with warm Hue, high Value, high Chroma and strong contrast feels convex and bulgy, so it seems larger. Conversely, the color with cold Hue, low Value, low Chroma and weak contrast feels concave and shrinkable, so it seems smaller. Color can also impact people's emotion. For example, light and pure color feels pastel and sweet. Heavy and pure color feels vivid and intense. Bright color feels Feminine, beautiful and magnificent. Dark and light color feels spiritless and vapid. Dark and heavy color feels Neuter and steady. Dark and light color feels quiet and even a little depressive.

Using Munsell color system, we can easily select suitable colors coincide with aesthetic preference and psychological feeling for garment design.

1.3 Research on Human Body Shapes and Garment Fitting

Research on human body shapes and Garment Fitting is the basis of garment design. In this part, we will introduce the existing research results.

1.3.1 Research of human body shapes based on Anthropometric measurements

Body shape analysis has become especially significant for satisfying the personalized requirements of a target population in garment design and mass customization. By classifying body shapes of a specific population, consumer products such as clothing, can be designed and produced more accurately and individually.

At present, information about body sizes and shapes is usually obtained from anthropometric data. During an anthropometric survey, many different body dimensions can be measured on each individual, resulting in thousands of data points. These data should be analyzed so as to identify the significant dimensions, which can be used to divide the target population into different clusters each having similar body dimensions. These significant body dimensions are known as key dimensions [18]. The first scientific study of body measurements using key dimensions for garment design was presented in 1941 by O'Brien and Shelton [18]. They used a bivariate distribution technique to develop the sizes according to bust and hip girth. Later, Otieno [19] classified children's body shapes according to two levels of key dimensions, such as height and bust girth for upper body garments and hip girth for lower body garments. Hsu [20] applied a bust-to-waist ratio approach to develop body measurement charts for improving female clothing manufacturing.

In practice, different body positions have different morphological features. Therefore, the existing classification criteria are often rough and the fitting level to a specific body shape is not high enough. In addition, the existing body classifications are mainly realized by using classical statistical methods such as factorial analysis, principal component analysis and regression analysis [21-28], and classical data mining techniques such as clustering classical decision tree and neutral network [29]. However, in garment design, designers usually describe body shapes using linguistic terms such as fat or thin, tall or short, etc. The classical methods often lead to unsatisfactory results since they cannot be used to process human perception effectively.

Since these linguistic terms reflect designer's conventional expressions describing their imprecise and vague perceptions, linguistic variables and fuzzy techniques [30, 31] are very suitable for dealing with this situation. On the basis of this principle, we tried to classify body shapes by using fuzzy clustering method and obtained dynamic clusters [32], but these results are sometimes quite different from the real situation in garment design. In practice, experienced designer's knowledge and perception, usually leading to very relevant body shape classification results in terms of design styles and other style elements, have never been exploited in the existing clustering algorithms.

According to the designer's experience, a relevant classification of body shapes should be sensitive to the overall morphological features of the target population. Rough set theory, proposed by Pawlak, has become a well-established mechanism for uncertainty management in a wide variety of applications. Particularly, rough sets have a strong ability of knowledge classification. Therefore, by combining the different advantages of two methods, we propose a fuzzy rough set-based method for analyzing key dimensions and characteristic indices of various body positions in order to accurately classify the shapes of various body positions of a given population. Sensory data on human body shape perception, provided by design experts, have also been integrated into the proposed classification method.

1.3.2 Research on Garment Fitting

Garment fitting has been regarded for a long time as one of the most important objective in garment design. In the Oxford Dictionary [6], "Fitting" is defined as the ability to be the right shape and size. In apparel field, the definitions of fitting vary from time to time, depending on fashion culture, industrial norm and individual perception of fitting [6]. As a complex property, garment fitting is closely related to comfort [33] and affected by fashion, style and many other factors [34].

Garment fitting does not only involve the body shape and the fabric properties which affect clothing drape and appearance but also include a social message, fashion, body cathexis, clothing physical dimensions, and so on. Garment fitting can be assessed by subjective and objective evaluation methods.

1.3.2.1 Subjective evaluation of garment fitting

Since garment fitting is based on various factors such as physical comfort, psychological comfort and appearance, and so on, understanding fitting from a consumer's perspective is very complex. Garment fitting is also influenced by fashion trends, personal preference and the intended end-use of the clothing. LaBat and DeLong [35] suggested two external factors (social message of the ideal body and fashion figure in the industry) and two personal factors (body cathexis and physical dimensional fitting of clothing) which have impacts on consumer's satisfaction for garment fitting.

In 1993, Shen and Huck [36] developed a subjective scale, containing 25 items divided into three categories: overall fitting, bodice front fitting and bodice back fitting. For each item, nine responses were possible, ranging from "much too tight" to "much too loose". The middle position for each fit criterion shows a good fit. Yu et al. [6] have applied this scale for the fit evaluation of men's jackets.

1.3.2.2 Objective evaluation of garment fitting

Objective evaluation techniques of garment fitting are performed by comparing the difference of two garment appearances, obtained from various pattern constructions and methods of assembly, without making any human assessment. This comparison is mainly based on optical methods, such as somatometry and moire topography, which capture the clothing images using a non-contact approach. By using image analysis, the feature lines of a 3D garment can be quantitatively characterized and compared with another one.

At present, various technologies have been developed for displaying clothing appearance in a simulated 3D form. These novel systems can provide a remote communication tool between industrial partners for communications on the 3D clothing fit, based on the clothing images. This may lead to more efficient and effective decision making in the process of product development and quality control.

1.3.2.3 Combination of subjective and objective evaluation methods

The above methods have advantages and disadvantages. The subjective approaches are still very imprecise for communications since the standardization of garment fitting remains a complex and controversial subject. The objective approaches do not always express the real feeling of wearers since they do not deal with any human experience.

Thus, some researchers tried to combine the methods of subjective and objective evaluations. For example, Y. Chen, et al [30] presented a new method for optimizing the estimation of ease allowance of a garment using fuzzy logic and sensory evaluation by combining subjective and objective evaluation methods. This aggregated result can further improve the wearer's fitting perception of a garment and adjust the compromise between the style of garments and the fitting comfort sensation of wearers.

1.4 General Notions of Recommendation Systems

Recommendation is a decision making strategy for users under complex information environments [37]. Recommendation system is an advanced business intelligence platform based on massive data mining for providing personalized decision support and information service to users. Being different from portal sites and search engines, a recommendation system can filter the users' interest points from large amount of dynamic information and intelligently recommend probably required information to users in conjunction with users' profile description and historical record without users' search operation by studying users' preferences and proceeding personalized computation.

A good recommendation system cannot only offer personalized services but also can establish close relation with users relied on recommendation.

1.4.1 Existing recommendation systems

The pioneer recommendation system is established by Goldberg, et al, in 1992 [38]. It filters and retrieves papers for users based on the definite relationship between user groups. The current recommendation system generally covers three important modules: users modeling module, recommended object module and recommendation algorithm module (Figure 1-7).

The utilization of efficient and accurate recommendation techniques is very important for a system that will provide good and useful recommendation to its individual users. The typical recommendation algorithms include Content-Based Filtering (CBF) [39], Collaborative Filtering (CF) [40], Association Rule-Based Recommendation (ARBR) [41], Utility-Based Recommendation (UBR) [42], Knowledge-Based Recommendation (KBR) [43] and Hybrid Filtering (HF) [44], and so on.

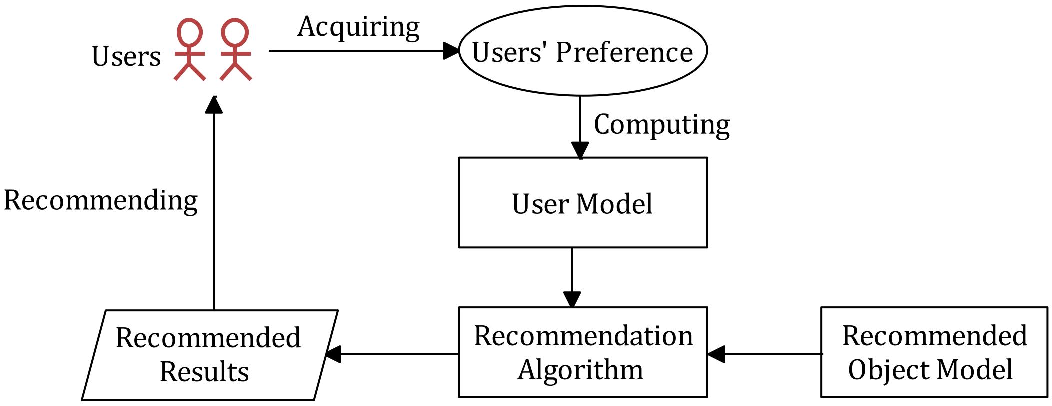


Figure 1-7 A general model of recommendation system

1.4.2 Existing recommendation systems in apparel industry

In apparel industry, recommender systems have also attracted much attention for realizing personalized garment design and providing fitting garment products. Besides the mentioned methods, researchers also presented other algorithms to develop various garment recommendation systems.

In the study of products design or clothing recommendation, researchers made a lot of work. For instance, Jung [45] set up a garment design recommender agent system by using the extraction of representative sensibility and combining collaborative filtering and content-based filtering. Wong [46] developed a fashion mix-and-match expert system using fuzzy screening approach to provide customers with professional and systematic mix-and-match recommendations automatically. In his another paper [47], he proposed a decision support tool for fashion coordination through the integration of the knowledge-based attribute evaluation expert system and the Takagi–Sugeno Fuzzy Neutral Network (TSFNN). This paper also proposed a fuzzy clustering technique and a new hybrid learning algorithm combining the PSO and GA techniques so as to reduce the coordination rules and the training time for the TSFNN. Jung [48] and Ajmani [49] respectively explored different ontology-based fashion recommender systems. Jung's system applied hybrid collaborative filtering and content-based filtering to discovery knowledge of user preference. Ajmani presented a content-based method using probabilistic multimedia ontology. Yang [50] presented a case study of an on-line system that recommends apparels based on rules gotten from decision tree mining and experienced dressing knowledge. Li [51] studied a sizes recommendation system based on analytic hierarchy process (AHP) and wavelet neutral network according to the different varieties of clothing and specific anthropometric data. P.Y.

Mok [52] proposed a customized garment design system by using interactive genetic algorithm (IGA) for non-professional users (general customers) to create their preferred garment designs in a user-friendly way.

The previous fashion recommendation systems mainly focus on the relations between products and consumers and rarely deal with human perception and emotion on fashion products. In fact, human perception plays a vital role in garment design. Thus, some researches proposed perception-based recommendation systems. For example, Zeng, et al. [53] proposed a perception-based recommender system for supporting garment designers, which can offer some recommendation suggestion. However, these systems cannot store successful knowledge and cannot also self-adjust or modify recommended results automatically if a user is not satisfied with recommendation results.

1.5 Foundation of a recommendation system for apparel

In garment recommendation's research, people have done a great quantity of work on contents and methods. The majority of the existing work focused on technological development for virtual garment assembling and mainly is used in e-commerce, while human's professional knowledge on design is rarely processed. In practice, for real garment design, many young designers don't always know what products are more suitable for the designed object. However, high-level designers had already collected a very rich knowledge for different domains of garments, especially personalized garments. These experiences and knowledge should be exploited in the future development of virtual garment prototypes and provide recommend suggestion for young designers according to design needs by an appropriate pattern or system. Besides, multiple experts' knowledge-based personalized recommendation would be more effective from a person's experience in apparel mass customization.

It is for this reason that we plan to develop designers-oriented garment recommendation system. In my subject, we will first establish dynamic design knowledge base for garment designers. The designers' experience will be retained in the knowledge base and spread so as to improve the quality and efficiency for garment design. On this basis, we will develop an intelligent recommendation system to garment designers for designing new personalized garment products. It will enable to provide scientific and reasonable suggestion on garment design process for young designers, and formalize and exploit professional knowledge of designers for quickly delivering small series customized garment design schemes according to specific measurements and preferences.

In addition, we try to develop self-adjusting and feedback function, which can automatically adjust design schemes according to users' feedback information until satisfaction.

CHAPTER 2 DATA ACQUISITION AND FORMALIZATION

In this chapter, we will present two data acquisition methods, including human body measurements from 3D scanning and sensory evaluation on body shapes and garment fits, performed by experienced designers according to their professional knowledge. For this purpose, a number of experiments are designed. Finally, the acquired data are mathematically formalized in order to set up models in the following chapters.

2.1 Acquisition of anthropometric data (Experiment 1)

As my thesis focuses on young women's jeans design, we only need the measurements related to women's lower body positions. The general principle can be easily adapted to other body positions and other garment types.

2.1.1 Key dimension measurements of the lower body position

As we know, of all body measurements, only key dimensions are significant for a specific body shape and a specific garment. For pant design, the selection of key dimensions will permit to effectively classify the lower body shapes of different consumers.

According to the knowledge of fashion designers, the lower body shape related to garment design is generally described by the shapes of several key body positions, including waist shape, hip shape, abdomen shape, leg length, thigh shape and calf shape. They can be characterized using the measurements of the vertical dimensions (Stature (S), Waist Height (WH), Crotch Height (CH), and the horizontal dimensions (Waist Girth (W), Hip Girth (H), Abdomen Girth (A), Thigh Girth (T), Calf Girth (C)). These measurements are called key body dimensions of the lower body [54, 55], which constitute quantitative a measuring vector (Unit: cm): $\mathbf{measure} = (S, WH, CH, W, H, A, TG, CG)$. Their descriptions are listed in Table 2-1.

Table 2-1 Description of selected body measurements

Measurements	Abbr.	Description	Diagram
Stature	*S*	The vertical distance from vertex to ground in standing posture.	
Waist Height	*WH*	The vertical distance from waistline to ground in standing posture.	
Crotch Height	*CH*	The vertical distance from crotch to ground in standing posture.	
Waist Girth	*W*	The length of measuring around the slenderest part of waist horizontally.	
Hip Girth	*H*	The length of measuring around the fullest part of hip horizontally.	
Abdomen Girth	*A*	The length of measuring around the fullest part of abdomen horizontally.	
Thigh Girth	*TG*	The length of measuring around the fullest part of thigh horizontally.	
Calf Girth	*CG*	The length of measuring around the fullest part of calf horizontally.	

2.1.2 Identification of characteristic indices on lower body position

In garment design, the differences and ratios of body measurements are generally more significant than direct ones for classification of human body shapes with different heights. In the national garment size standard GBT1335.2-2008 of China, lower body shapes are classified according to hip-waist difference. In fact, body shapes with identical girth difference but different heights often look different, so we also consider girth-girth ratio, height-height ratio and girth-height ratio beyond girth difference. According to garment size standard and experts' analysis, we selected 15 lower body indices as follows.

(1) Waist shape index

The index ws is used to describe the entire waist shape.

$$ws = \frac{W}{S} \tag{2-1}$$

ws can reflect the fat or thin level of waist, and the higher the ws value is, the more plump waist looks.

(2) Hip shape indices

Hip shape can be described by the combination of a difference hs_1, two ratios hs_2 and hs_3.

$$hs_1 = H - W, \qquad hs_2 = \frac{H}{W}, \qquad hs_3 = \frac{H}{S} \tag{2-2}$$

hs_1 and hs_2 can describe flat or raised level of hip, and the higher hs_1 or hs_2 value is, the more raised hip is. hs_3 can describe fat or thin level of hip, and the higher hs_3 value is, the more plump hip looks.

(3) Abdomen shape indices

Abdomen shape can be described by a difference as_1 and two ratio as_2 and as_3.

$$as_1 = A - W, \qquad as_2 = \frac{A}{W}, \qquad as_3 = \frac{A}{S} \tag{2-3}$$

as_1 and as_2 can describe flat or convex level of hip. The higher as_1 or as_2 value is, the more convex abdomen is. as_3 can describe large or small level of abdomen, and the higher as_3 value is, the more plump abdomen looks.

(4) Leg length indices

Two ratios ll_1 and ll_2 are used to describe proportion of body shape.

$$ll_1 = \frac{CH}{S}, \qquad ll_2 = \frac{WH}{S} \tag{2-4}$$

ll_1 can describe proportion of leg, the higher ll_1 value is, the longer leg seem. ll_2 can characterize harmony of lower body, and the closer ll_2 to golden ratio 0.618, the better harmony of body shape is.

(5) Thigh shape indices

Three ratios are used to describe thigh shape.

$$ts_1 = \frac{TG}{W}, \qquad ts_2 = \frac{TG}{H}, \qquad ts_3 = \frac{TG}{S} \tag{2-5}$$

ts_1 and ts_2 can describe thick or thin level of thigh, and the higher ts_1 or ts_2 value is, the more thick thigh looks; ts_3 can describe accumulation level of thigh fat, and the higher ts_3 value is, the more thigh fat is.

(6) Calf shape indices

There ratios are used to describe calf shape.

$$cs_1 = \frac{CG}{W}, \qquad cs_2 = \frac{CG}{H}, \qquad cs_3 = \frac{CG}{S} \tag{2-6}$$

cs_1 and cs_2 can describe thick or thin level of calf, and the higher cs_1 or cs_2 value is, the more thick calf looks; cs_3 can describe accumulation level of calf fat, and the higher cs_3 value is, the more calf fat is.

Obviously, the increase of each index from small to large can describe the change of relevant body shape of body position from small to large though the criteria are different.

Since each index approximately satisfies normal distribution, it can be normalized by the following z-score normalization (Zero-Mean Normalization) method [56].

$$x' = \frac{x - \sigma}{sd} \tag{2-7}$$

where x is the initial data, x' is the normalized data, σ is the mean of data and sd is the standard deviation.

All the normalized indices are denoted by initial symbols and let the set of body indices be assigned as follow:

$SI = \{ws, hs_1, hs_2, hs_3, as_1, as_2, as_3, ll_1, ll_2, ts_1, ts_2, ts_3, cs_1, cs_2, cs_3\}$.

The set can effectively describe the human body shape and permit to perform further studies such as body shape classification.

2.1.3 Identification of experimental samples

Generally, it usually requires a great quantity of data to form correct classes. However, the number of data is limited because of the time-consuming and complex measuring process. In this experiment, 125 young women from 18 to 25 in central China were selected randomly and measured by the 3D body scanning.

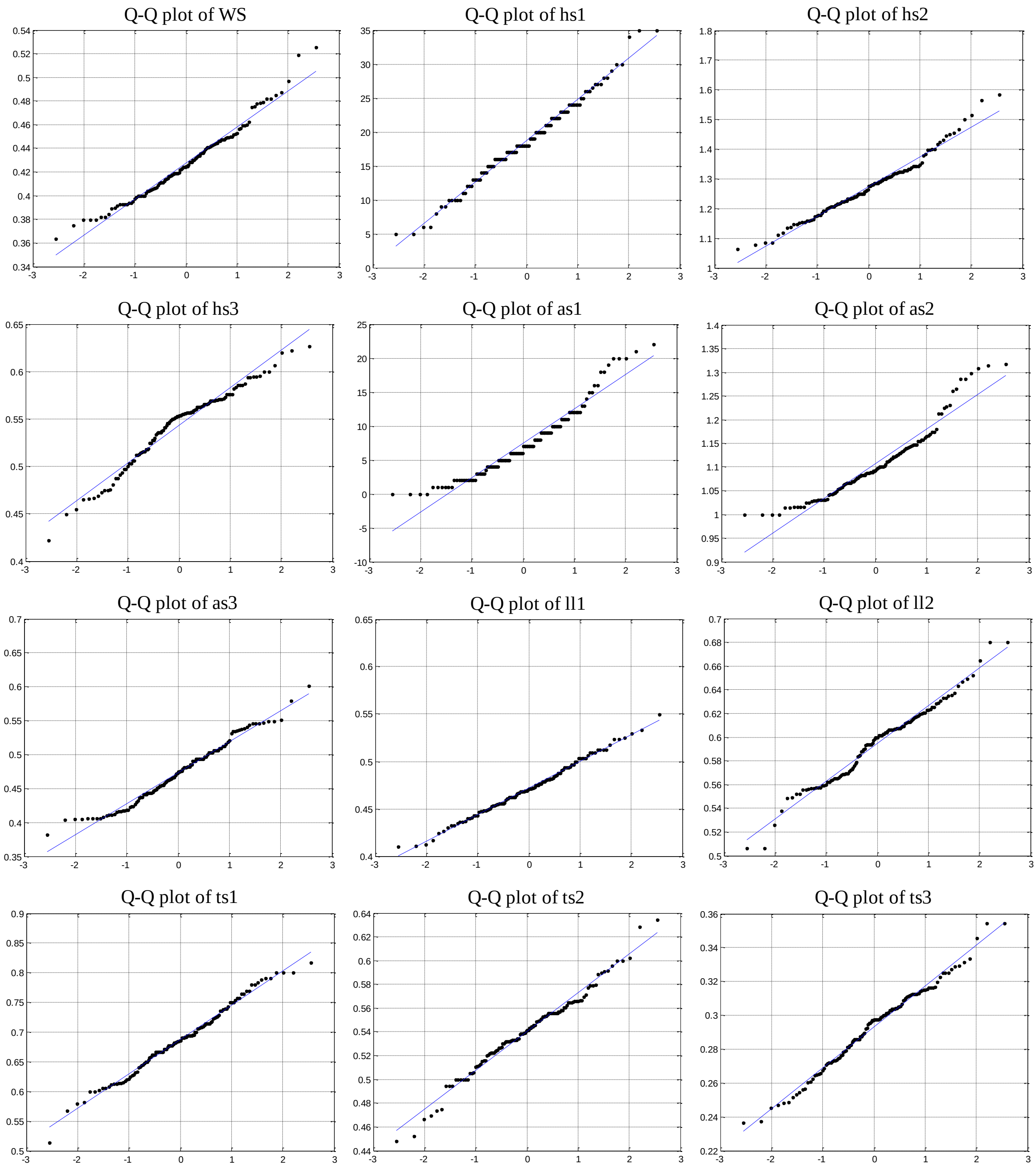
As the number of the experimental samples is much smaller than the target population, it is necessary to check the validity and representativeness to ensure that the results can be extrapolated to the population. According to the general features of human body data, the effective methods are outlier and normal distribution examination.

In a group of data $x_1, x_2, \dots, x_n$, x_i $(i = 1, 2, \dots, n)$ is an outlier if it satisfies

$$|x_i - \sigma| > 3sd \tag{2-8}$$

where σ is the mean of data and sd is the standard deviation.

From the index values calculated from the initial body measurements, we found 7 outliers and the Q-Q plots (Q-Q plot is a scatter plot on which the quantiles of standard normal distribution are taken as vertical coordinates and the sample values are taken as horizontal coordinates; the sample data roughly satisfy normal distribution if all the points on the Q-Q plot approximately lie on a line which's slope is the standard deviation and intercept is the mean value) [57] of various index values of other samples are shown in Figure 2-1.



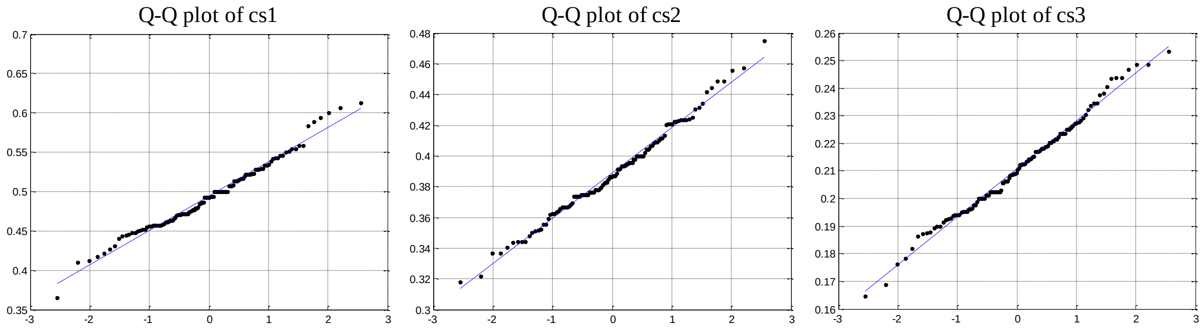


Figure 2-1 Normal distribution testing of body data

From the results of Q-Q plots, we can find that these data roughly satisfy normal distributions except a few kurtosis deviations. Ultimately, 118 groups of characteristic indices will be used as experimental samples.

2.2 Acquisition of technical parameters of fabrics (Experiment 2)

According to the properties of denim fabrics [58-61] and experts' suggestion and the existing experimental conditions, we select 11 technical parameters of fabrics, including "Fiber-Composition(tp_1)", "Gram-Weight(tp_2)", "Thickness(tp_3)", "Warp-Density(tp_4)", "Weft-Density (tp_5)", "Warp Breaking-Strength (tp_6)", "Weft Breaking-Strength (tp_7)", "Warp Elongation (tp_8)", "Weft Elongation (tp_9)", "Water-Permeability (tp_{10})", and "Air-Permeability(tp_{11})".

2.2.1 Measuring the technical parameters of fabrics

In this experiment, we first select 25 denim fabrics (without finishes) commonly used in jeans from the associated industrial company, and number them from 1 to 25 respectively. According to the standard measuring methods supported by the Chinese Nation Textile Standard, we measure the 11 related technical parameters by using several apparatuses with high precision (Appendix 2).

By repeating the fabric measurements for several times, we find that the air-permeability of fabric can be measured only through a suitable aperture and the majority of air-permeability measures can only be detected with an aperture of 2mm.

2.2.2 Identification of fabric samples

As the number of fabric samples is still high (25) for a human sensory evaluation, we need to reduce it to a level accepted by sensory experiments (around 10 samples). In this situation, we can realize it by performing a clustering algorithm. By discussing with fabric experts, we find that "fiber composition" is the most important key index to distinguish fabrics. If we only consider the fiber composition in fabrics without taking into account the rate of each type of fibers, these 25 kinds of fabrics can be further regrouped into 6 classes, including {1~6, 22, 24, 25 (Cotton + Polyester + Spandex)}, {7, 8, 11~13, 20, 21, 23 (Cotton + Polyester + Spandex + Viscose)}, {9, 10 (Cotton)}, {14, 15 (Lyocell)}, {16, 17 (Lyocell + Cotton)} and {18, 19 (Cotton + Spandex)}. However, in practice, we cannot consider fiber compositions only for clustering of fabric samples because the other technical parameters ($tp_2 \sim tp_{11}$) could be also relevant. At this stage, we just remove tp_{11} (air permeability) because its measures are not stable, and then perform the clustering of fabrics with the other nine stable and normalized parameters ($tp_2 \sim tp_{10}$) by using the λ-fuzzy cluster analysis (fuzzy matrix operations, fuzzy partitions) [62] and the corresponding dynamic clustering graph is below.

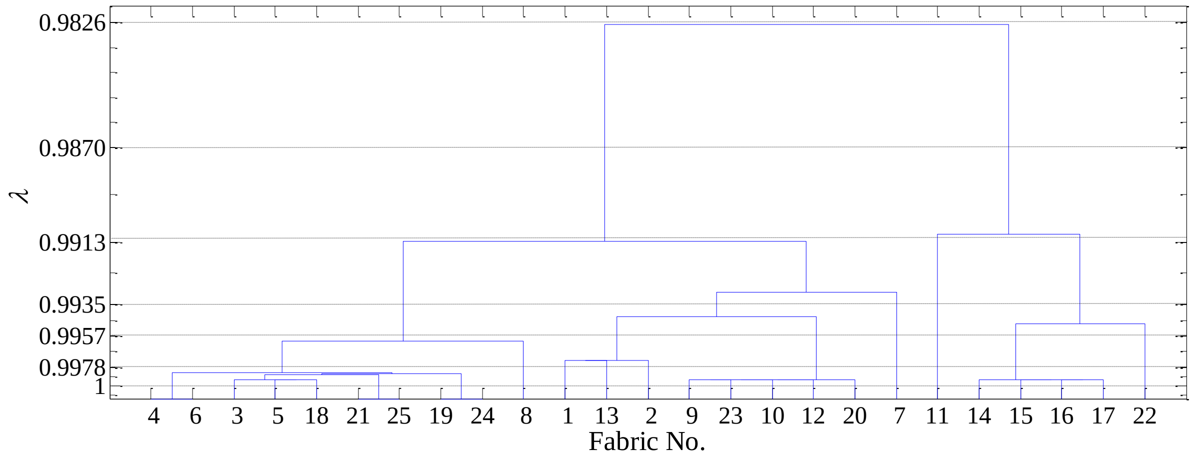


Figure 2-2 λ-fuzzy cluster analysis of fabrics with tp_2 to tp_{10}

From this cluster graph, we can identify the following different clusters if the values of cutting (threshold) λ for fuzzy partitions are different. Some typical cases are given below.

1) If $\lambda = 0.9826$, all the samples are clustered into one class with tp_2 to tp_{10}.

In this case, we only consider the classification results with fiber composition (tp_1). All the samples are clustered into 6 classes as we found previously. This case is not significant because, in practice, we need to consider the other relevant fabric parameters for clustering.

2) If $\lambda = 0.9870$, all the samples are clustered into 2 classes with tp_2 to tp_{10}:

{1~10, 12, 13, 18~21, 23~25} and {11, 14~17, 22}.

By combining with the results of fiber composition (6 classes with tp1), we obtain 8 classes:

{1~6, 24, 25}, {7, 8, 12, 13, 20, 21, 23}, {9, 10}, {11}, {14, 15}, {16, 17}, {18, 19} and {22}.

3) If $\lambda = 0.9913$, we obtain the same results as 2) (8 classes).

4) If $\lambda = 0.9935$, we obtain 11 classes:

{1, 2}, {3~6, 24, 25}, {7}, {8, 21}, {9, 10}, {11}, {12, 13, 20, 23}, {14, 15}, {16, 17}, {18, 19} and {22}.

5) If $\lambda = 0.9957$, we have 12 classes:

{1, 2}, {3~6, 24, 25}, {7}, {8, 21}, {9, 10}, {11}, {12, 20, 23}, {13}, {14, 15}, {16, 17}, {18, 19} and {22}.

6) If $\lambda = 0.9978$, we have 15 classes:

{1}, {2}, {3~6}, {7}, {8}, {9, 10}, {11}, {12, 20, 23}, {13}, {14, 15}, {16, 17}, {18, 19}, {21}, {22} and {24, 25}.

7) If $\lambda = 1$, we have 24 classes. This case is less significant due to the fact that most of these classes are composed of single data.

The other values of λ give the same results as the previous typical cases. In fact, λ-fuzzy cluster analysis enables to largely reduce the problem of clustering by determining the significant numbers of classes (not unique). In our study, according to the analysis of each typical case, we just need to consider the four following cases: $\lambda = 0.9870$ or $\lambda = 0.9913$ (8 classes), $\lambda = 0.9935$ (11 classes), $\lambda = 0.9957$ (12 classes), $\lambda = 0.9978$ (15 classes).

Next, for each of these four cases, we use the statistical method for precisely determining the best number of classes from these four cases.

According to the general principle of classification, a partition of data is good if the distances between different classes are large and the distances of data inside each class are small. This principle is formalized as follows.

Let $U = \{x_1, x_2, \ldots, x_n\}$ be a sample space of fabrics and each sample x_i has m technical parameters. Each sample can be represented by a vector $\boldsymbol{x}_i = (x_{i1}, x_{i2}, \ldots, x_{im})$ $(i = 1,2, \ldots n)$, where x_{ij} $(i = 1,2, \ldots, n; j = 1,2, \ldots, m)$ expressed the value of the j-th technical parameter of the i-th fabric.

Denote $\bar{x}_k = \frac{1}{n}\sum_{i=1}^{n} x_{ik}$ $(k = 1,2, \ldots, m)$, thus, $\bar{\boldsymbol{x}} = (\bar{x}_1, \bar{x}_2, \ldots, \bar{x}_m)$ is the center vector of all samples.

Let the number of classes corresponding to λ be r and the number of samples in the j-th class be n_j. The i-th sample in the j-th class is denoted as

$\boldsymbol{x}_i^{(j)} = \left(x_{i1}^{(j)},\ x_{i2}^{(j)}, \dots, x_{im}^{(j)}\right)\ (i = 1,2, \dots, n_j)$.

Denote $\bar{x}_k^{(j)} = \frac{1}{n_j}\sum_{i=1}^{n_j} x_{ik}^{(j)}\ (k = 1,2, \dots, m)$, thus, $\bar{\boldsymbol{x}}^{(j)} = \left(\bar{x}_1^{(j)},\ \bar{x}_2^{(j)}, \dots, \bar{x}_m^{(j)}\right)$ is the center of the j-th class.

We constitute a F-Statistical value below and then perform F-test [63].

$$\boldsymbol{F} = \frac{\sum_{j=1}^{r} n_j \left\|\bar{\boldsymbol{x}}^{(j)} - \bar{\boldsymbol{x}}\right\|^2 /(r-1)}{\sum_{j=1}^{r}\sum_{i=1}^{n_j}\left\|\boldsymbol{x}_i^{(j)} - \bar{\boldsymbol{x}}^{(j)}\right\|^2 /(n-r)} \tag{2-9}$$

where $\|\cdot\|$ expresses the Euclidian distance between two vectors.

We can prove that $\boldsymbol{F}$ follows the F-distribution with the degrees of freedom $(r-1)$ and $(n-r)$. Obviously, the numerator of $\boldsymbol{F}$ can express the averaged distance of various classes, and denominator of $\boldsymbol{F}$ can express the averaged distance of samples inside each class. Therefore, to a certain level α (confidence coefficient is $1-\alpha$), the partitions satisfying $\boldsymbol{F} > F_\alpha(r-1, n-r)$ are acceptable. The optimal partition corresponds to the maximal relative value $\eta_\alpha = (\boldsymbol{F} - F_\alpha)/F_\alpha$.

The F-Statistical value and the corresponding critical value F_α of each of the four cases are shown in Table 2-2.

Table 2-2 F-Statistics and critical values of different partitions

The number of classes	$\boldsymbol{F}$	$F_{0.05}$	$\eta_{0.05}$	$F_{0.025}$	$\eta_{0.025}$
8	3.3738	2.6143	0.2905	3.1556	0.0692
11	3.3471	2.6022	0.2863	3.1468	0.0636
12	3.7755	2.6347	0.4330	3.1975	0.1808
15	3.8982	2.8647	0.3608	3.5504	0.0980

From Table 2-2, it can be easily found that all of four cases are acceptable and the best number of classes is 12 no matter $\alpha = 0.05$ or $\alpha = 0.025$.

The details of each class are shown in Table 2-3.

Table 2-3 The ultimate clustering results of fabrics

Fiber composition	Class of fabrics
Cotton+Polyester+Spandex	{1, 2}, {22}, {3, 4, 5, 6, 24, 25}
Cotton+Polyester+Spandex+Viscose	{7}, {8, 21}, {11}, {12, 20, 23}, {13}
Cotton	{9, 10}
Lyocell	{14, 15}
Lyocell+Cotton	{16, 17}
Cotton+Spandex	{18, 19}

In each class, we select a representative fabric which is the closest to the center of the class. Ultimately, we take 12 typical fabrics (1, 7, 8, 9, 11, 13, 14, 16, 18, 22, 23, and 24) as experimental samples. The pictures of the samples are shown below.

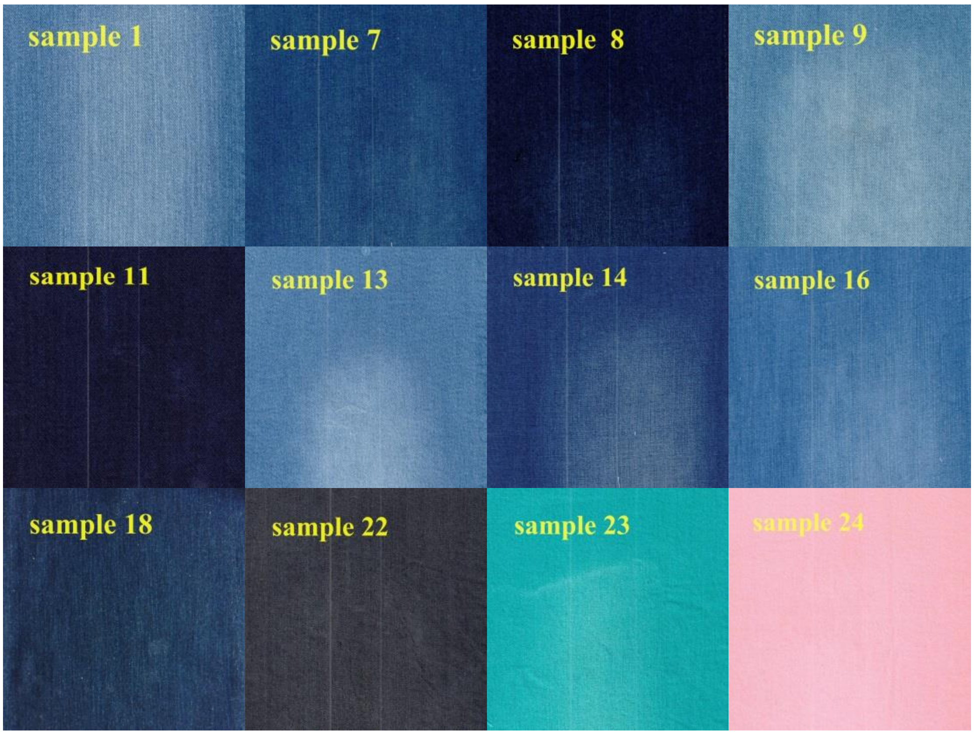


Figure 2-3 The pictures of 12 selected representative fabric samples

2.3 Acquisition of designers' knowledge

"Knowledge" is the achievement gained when human recognizes the objective world in practice, and is a familiarity, awareness or understanding of someone or something, such as facts, information, descriptions, or skills, which is acquired through experience or education by perceiving, discovering or learning [64]. Knowledge acquisition involves complex cognitive processes including perception, communication and reasoning. Therefore, knowledge is also said to be related to the capacity of acknowledgment in human beings [65] and more suited to be acquired by perceptual methods [66]. In my thesis, we acquire garment designers' knowledge by using the sensory evaluation technique.

2.3.1 General notions about human perceptions

"Perception" (from the Latin perceptio, percipio) is the organization, identification, and interpretation of sensory information in the human brain so as to represent and understand the environment [67]. Perception is not the passive receipt of signals, but is shaped by learning, memory, expectation, and attention [68].

2.3.1.1 Process and components of human perceptions

The process of perception begins with an object in the real world, termed the distal stimulus or distal object. By means of light, sound or another physical process, the object stimulates the body's sensory organs. These sensory organs transform the input energy into neutral activity – a process called transduction [69].

Perception can be split into two processes. The first one is to process the sensory input, which transforms the low-level information into higher-level information (e.g., shape extraction for object recognition). The second one is to make connection with a person's concepts and expectations (knowledge) and selective mechanisms (attention) that influence perception.

Generally, perception includes three components.

(1) **The perceiver**, the person who becomes aware about something and comes to a final understanding. Three factors can influence his or her perceptions, including experience, motivational state and emotional state.

(2) **The target**, the person or object that is being perceived or judged.

(3) **The situation** also greatly influences human perceptions because different situations may call for additional information about the target.

2.3.1.2 Types of human perceptions

Human generally takes in information through five senses [70] including vision, touch, hearing, smelling, and taste by five sense organs. As information comes in through our senses, various factors influence what actually continues on through the perception process [71].

(1) Vision and visual perception

The majority of human's activities, such as image, experience, and knowledge, etc, are related to vision. Particularly in information society, as we know that a plenty of information from the outside world is acquired by vision.

Visual perception, i.e. the sense of sight, is the ability to interpret the surrounding environment by processing information that is contained in visible light.

(2) Touch and tactile perception

Touch is a somesthetic sense when contacting objects by skins and it covers fine touch and crude touch [72]. Fine touch, also called discriminative touch, is a sensory modality that allows a subject to sense and localize touch. Crude touch, also called non-discriminative touch, is a sensory modality that allows the subject to sense that something has touched them, without being able to localize where they were touched. As fine touch normally works in parallel to crude touch, a person will be able to localize touch until fibres carrying fine touch have been disrupted. Then the subject will feel it, but be unable to identify where they were touched.

Tactile perception is the general term of touch, slide and pressure sense and it is the sense of skin to external stimulus such as temperature, humidity, ache, pressure, shake, and so on.

(3) Hearing and aural perception

Hearing is the sense to perceive sound. Like touch, audition requires sensitivity to the movement of molecules in the world outside the organism. Both hearing and touch are types and mechanosensation [73].

Aural perception is the ability to perceive sound by detecting vibrations [74], and changes in the pressure of the surrounding to medium through time, through an organ such as the ear.

(4) Smelling and osphretic perception

Smelling is the sense to detect chemical stimulus by the olfactory epithelium of nose. Osphretic perception is the ability of smelling an odor.

(5) Taste and taste perception

Taste is the sense produced when a substance in the mouth reacts chemically with taste receptor cells located on taste buds in the oral cavity, mostly on the tongue.

Taste perception is the ability to detect flavors by tongue and it includes five established basic tastes: sweetness, sourness, saltiness, bitterness and umami [75, 76].

2.3.2 Human Perception in garment design

Human perception related to a fashion product’s design is mainly based on aesthetics (e.g. theme, style, accessories, texture of fabric, …), comfort (e.g. garment fitting, fabric handle, …), functionality (warmth protection, moisture absorption, …), structure, and so on. Therefore, visual perception and tactile perception are regarded as two key human perceptions in garment design.

Human perception in garment design is a cycling process of identifying, organizing and interpreting sensory information (Figure 2-4).

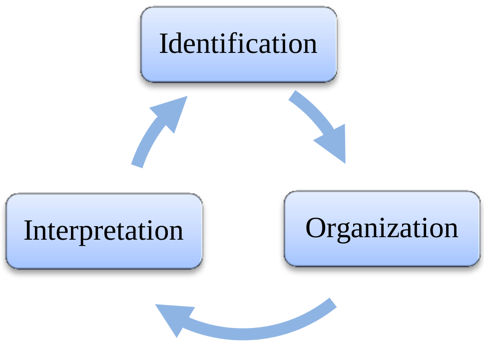


Figure 2-4 The perception process

Identification is the first stage of the perception process, in which people focus attention on certain incoming sensory information and tend to find salient things that are visually or tangibly stimulating and things that meet their needs or interests. Although cognitive processes cannot be observed directly, they are reflected in the pattern of gaze behavior [77].

Organization is the second stage of the perception process, in which garment designers sort and categorize information that they perceive based on innate and learned cognitive patterns. They sort things into patterns by using three ways including proximity, similarity, and difference.

Interpretation is much more deliberate and conscious than two first ones. In this process, garment designers assign meaning according to their experiences using mental structures known as schemata. Schemata are like stored databases, in which related information is used to interpret new experiences. It is important to be aware of schemata because designers' interpretations affect their design behavior.

2.3.3 General notions of sensory evaluation

It is necessary to use a standardized and systematic research method to extract reliable information from human perception. Sensory evaluation is just an appropriate method to do that. In an enterprise, the sensory evaluation on products, processes and markets are strongly related to human knowledge.

2.3.3.1 Basic concept of sensory evaluation

The concept of sensory evaluation was firstly presented by Amerine in food industry [78], and the purpose is to obtain the consumers' subjective experience on foods, such as the taste, color, shape, texture, packaging, etc. A definition of sensory evaluation (also called sensory analysis) which has been commonly accepted now is that it is a scientific discipline to be used to measure, analyze, evoke, and interpret the reactions to those characteristics of objective things as they are perceived by human perception [79]. It means the impression that somebody obtains from a certain product, environment or situation by all the senses of sight, touch, hearing, smell, taste as well as her cognition. It involves the measurement, evaluation, analysis and interpretation of the sensory properties of objective things perceived by general public or experts.

Nowadays, the concept of sensory evaluation (sensory analysis) has been expanded to a general scientific discipline that applies principles of experimental design to the use of human senses for the purposes of evaluating consumer products [80], and the approach has been applied in other industries [81-88] such as cosmetics, medicines, chemicals, textile and apparel, etc.

2.3.3.2 General process of sensory evaluation

Sensory evaluation generally involves the three following processes.

(1) Identification of sensory panels

Sensory evaluation is carried out by one or several sensory panels. A sensory panel is described as a group of testers organized to evaluate products on the basis of their perception. The sensory panelists are trained to describe their sensory experiences using words they generate in previous training sessions [89].

The sensory panels can be usually classified into the following five categories.

(a) Panels of domain experts

The panelists are trained to evaluate products and define evaluation criteria by using specific domain knowledge.

(b) Panels of quantitative analysis

The panelists are trained to evaluate products by using standard linguistic terms.

(c) Panels of free choice

The panelists are trained to evaluate the products by using their own words.

(d) Panels of specific consumers

The non-trained panelists are invited to evaluate the products under a specific experimental condition.

(e) Panels of random consumers

The non-trained panelists are selected randomly from consumers and asked to answer the pre-designed questionnaires.

The training level and specialized knowledge gradually increase from the panels of consumers to panels of experts, and they play different roles in sensory evaluation. In general, the selection of panelists should be strongly related to the concerned professional public (designers' panel, consumers' panel, producers' panel, …..).

(2) Design of sensory experiments

Scientific design of experiments is the guarantee of obtaining valid and reliable data. A standardized experiment generally includes explicit experimental objectives, typical experimental samples, scientific experimental methods and detailed experimental procedures. Generally speaking, the types of the panels and data characteristics are different if experimental objectives are different. Therefore, in design of sensory experiments we should first identify the sensory panels according to experimental objectives. Moreover, all the experimental samples have to be evaluated in the same way by each panelist. Particularly for experts, the training process is very vital. A sensory experiment generally includes three processes as follows [80].

(a) Effective testing

This type of testing is concerned with obtaining objective facts about products. It could range from basic discrimination testing (e.g. Do two or more products differ from each other?) to descriptive profiling (e.g. What are the characteristics of two or more products?). The type of panel required for this type of testing would normally be a trained panel.

(b) Affective testing

It is also known as consumer testing, this type of testing is concerned with obtaining subjective data such as preferences, or how well products are likely to accepted. Usually large (50 or more) panels of untrained personnel are recruited for this type of testing, although smaller focus groups can be utilized to gain insights into products. The range of testing can vary from simple comparative testing (e.g. Which do you prefer, A or B?) to structured questioning regarding the magnitude of acceptance of individual characteristics (e.g. Please rate the "style of garment": unfit/neutral/fit).

(c) Perception

Perception involves the biochemical and psychological theories relating to human sensations. By understanding the mechanisms involved, it is possible to explain why certain characteristics are preferred over others. In fact, there are at least three steps in the process. Firstly, the stimulus hits the sense organ and is converted to a nerve signal that travels to the brain. Then, the brain interprets, organizes and integrates the incoming sensations into perceptions. Finally, a response is formulated based on the subject's perceptions.

The basic function of sensory experiments is to have an effective and reliable test so as to provide the basis for correct and rational decision. Therefore, the appropriate test methods are also very important. A typical method is Points Scale Test, and namely a semantic differential method [90, 91] presented by Osgood and Luria in 1954. Using this method, we first establish a semantic space by formalizing and characterizing human perceptions on a specific product, where its word pair can form the two poles of the sensory axe when a concept is considered, and then select several evaluation measuring scales (e.g. five-points scale, seven-points scale and nine-points scale, …), which is usually expressed by some adjective words such as “very”, “fairy”, “rather”, “neutral”, and so on. It is possible to project every concept in the semantic space and give it an individual position. For example, description about softness of fabrics can be scaled on the softness axe by a pair of word “soft-hard” (Figure 2-5).

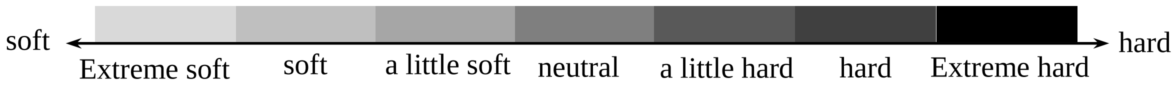


Figure 2-5 Seven-points semantic differential scale of fabrics softness

(3) Modeling of sensory data

Many methods have been developed to model sensory data. The early methods frequently used are based on statistics such as factor analysis, principal component analysis, linear regression analysis, correlation coefficient analysis, and so on. However, the drawbacks of the classical methods gradually appear in practice since they require certain and precise data while knowledge described by language is often uncertain and imprecise, and can only process determinate and complete datasets while different human perceptions are frequently unified and some data even are not easy to be acquired.

In this situation, non-classical set theory and intelligent techniques become appropriate approaches. In apparel field, many related research achievements have appeared. For instance, Xue [88, 89] researched the relations between handle and formability of suiting fabrics based on a Fuzzy-Genetic Model, and the relations between visual and haptic perceptions of textile products by developing a fuzzy neutral network. X. Chen, et al [30] optimized the estimation of ease allowance of a garment by using fuzzy logic and sensory evaluation. X. Zeng, et al [92] presented a fuzzy multi-criteria sensory evaluation method for designing new products meeting specific market requirements. They also gave a general methodology for analyzing fashion oriented textile products using sensory evaluation [93]. L. Wang， et al [94] presented a method permitting to determine the relationship between body measurements and human perception on morphology of body shapes by fuzzy method. X. Chen, et al [16] discussed virtual fabrics and its relation with the technical parameters of real fabrics by fuzzy decision trees.

2.4 Sensory Experiments in our research

In our study, the purpose of the sensory experiments is to acquire design knowledge by evaluating human bodies and virtual finished garment products, and obtaining the relations between body shapes and garment properties, and between fashion themes and garment properties.

2.4.1 Sensory panel and training

In our study, the sensory experiments are carried out by a panel of experts with fashion or textile design background since we need to set up an oriented-designer recommendation system. This panel is composed of fifteen experienced designers including six fashion designers (Group 1), six pattern designers (Group 2) and three fabric designers (Group 3), which can play different roles in different sensory experiments according to their knowledge structures. Fashion designers master knowledge of garment design and have good aesthetic experiences on garments, while pattern designers master knowledge of both body structures and garment structures, and fabric designers have rich sensory experiences on fabrics. In all sensory experiments, garment designers participated in multiple experiments except body shapes and sensory properties of fabrics, pattern designers participated in multiple experiments except colors and sensory properties of fabrics, and fabric designers only take part in the experiments related to fabrics.

Before each evaluation session, all panelists are invited to follow instructions for 30 minutes on the main purposes of various experiments, evaluation techniques and procedures, and interpretation of related concepts.

The training session organized for the panelists covers three Sections. 1) The first Section is the training of body shapes recognition by observing virtual pictures of 3D body scanning, which can help panelists to form unified recognition criteria. 2) The second Section is the training on understanding of the levels of themes, styles and colors by interviewing a number of relevant photographs, which help panelists to establish common concepts. 3) The third Section is the real touch and visual sensory training to training samples, which help the panelists to get familiar with all the descriptors and evaluation scales. The whole training session took about two hours.

2.4.2 Descriptions of related concepts

Before experiments, we need to give the basic descriptions of related concepts.

(1) Body shapes

As we are interested in the design of women's jeans only, six lower body positions are considered (described in experiment 1), and each body position can be evaluated using five scores: "Very Small (VS)", "Small (S)", "Middle (M)", "Large (L)" and "Very Large (VL)". Their combinations lead to 30 lower body shapes, described using the descriptors and signs of Table 2-4.

Table 2-4 The descriptors and signs describing lower body shapes

Body Position	Abbr.	very large	large	middle	small	very small
Waist Shape	WS	$WS^{(VL)}$	$WS^{(L)}$	$WS^{(M)}$	$WS^{(S)}$	$WS^{(VS)}$
Hip Shape	HS	$HS^{(VL)}$	$HS^{(L)}$	$HS^{(M)}$	$HS^{(S)}$	$HS^{(VS)}$
Abdomen Shape	AS	$AS^{(VL)}$	$AS^{(L)}$	$AS^{(M)}$	$AS^{(S)}$	$AS^{(VS)}$
Leg Length	LL	$LL^{(VL)}$	$LL^{(L)}$	$LL^{(M)}$	$LL^{(S)}$	$LL^{(VS)}$
Thigh Shape	TS	$TS^{(VL)}$	$TS^{(L)}$	$TS^{(M)}$	$TS^{(S)}$	$TS^{(VS)}$
Calf Shape	CS	$CS^{(VL)}$	$CS^{(L)}$	$CS^{(M)}$	$CS^{(S)}$	$CS^{(VS)}$

(2) Fashion themes

Generally, fashion theme is the value orientation, intrinsic character and artistic characteristics shown from the form and content a garment. In the important fashion events, fashion themes are often communicated to general public through fashion forecasting reports or seminars [95]. Different garments can express different fashion themes, and we need to identify the most typical themes related to design of women's jeans. The procedure includes three steps as follows.

(a) Collection and selection of keywords

By searching information from newspapers, fashion magazines, books, dictionaries, Internet, and discussing with garment design experts, we collected a great number of semantic words related to women's jeans. After the discussion with the panelists involved in our study, the words leading to semantic confusions are removed. Then, we preliminarily select 100 keywords.

(b) Clustering and Pairwise combination of keywords

Many synonyms and near-synonyms of the keywords describing women's jeans are regrouped by the panelists through a round table discussion. As a result, 100 fashion keywords are divided into 33 groups.

Next, we regroup the above keywords with opposite semanteme into pairs. During this procedure, the unpaired words are removed. In the end, we select representative words from synonyms and identify three pairs of semantically opposite keywords, which will be taken as fashion themes. They include "Neuter-Feminine", "Elegant-Wild" and "Traditional-Modern", whose descriptions are shown as follows. Some explanations and associated pictures are given below (All the pictures are from baidu.com).

Table 2-5 The descriptions of six themes

Fashion theme	Description	Associated pictures
Neuter/	suitable for men and women, and to weaken the characteristics of women	
Feminine	Expressing qualities or appearance traditionally associated with women	
Elegant/	pleasingly graceful and stylish in appearance or manner	
Wild	unrestrained	
Traditional/	long-established; classic; standard	
Modern	relating to the present or recent times as opposed to traditional; fashionable	

According to the semantic differential method [90], the 7-points scales of three pairs of fashion themes are shown in Figure 2-6.

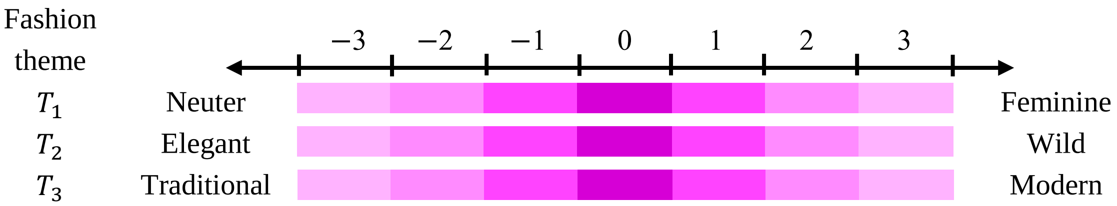


Figure 2-6 Semantic differential scales of fashion themes

(3) Garment properties

The garment properties include design style, fabric and color.

(a) Design style

Design style is composed of basic style elements, detail and accessory. All the design styles constitute a design styles base. For women's jeans, the descriptions of all style elements and their symbols are listed in Table 2-6.

Table 2-6 Style components, style elements and their symbols

Basic style component	Basic style element	Symbol	Detail component	Detail element	Symbol	Accessories	Symbol
Pattern	Skinny	$PATTERN_1$	Front-Pocket ($DETAIL_1$)	Crescent	$DETAIL_{11}$	no-Accessory	$ACCESSORY_0$
	Slim	$PATTERN_2$		Covered	$DETAIL_{12}$	Lace	$ACCESSORY_1$
	Straight	$PATTERN_3$	Back-Pocket ($DETAIL_2$)	Uncovered	$DETAIL_{21}$	Embroidery	$ACCESSORY_2$
	Loose	$PATTERN_4$		Covered	$DETAIL_{22}$	Fasteners	$ACCESSORY_3$
Waist Level	Low-Waist	$WAIST_1$	Front-Fly ($DETAIL_3$)	Fasteners	$DETAIL_{31}$	Rivets	$ACCESSORY_4$
	Regular-Waist	$WAIST_2$		Buttons	$DETAIL_{32}$	Diamonds	$ACCESSORY_5$
	High-Waist	$WAIST_3$	Side-Seam ($DETAIL_4$)	Hidden	$DETAIL_{41}$	Tassels	$ACCESSORY_6$
Leg Level	Tapered	LEG_1		Exposed	$DETAIL_{42}$	…	…
	Regular	LEG_2	Patchwork ($DETAIL_5$)	no-Patchwork	$DETAIL_{51}$		
	Boot-Cut	LEG_3		Patchwork	$DETAIL_{52}$		
	Wide-Bell	LEG_4	Broken-Hole ($DETAIL_6$)	no-Holey	$DETAIL_{61}$		
				Holey	$DETAIL_{62}$		

All of basic style elements, detail elements and accessories are called style elements. According to the modular design principle provided by fashion designers obtained from their experience, of all the basic style components and detail components, only one element is selected for each component. However, multiple accessories can be selected together.

(b) Color

As we focus on the design of jeans which are mainly pure color, we only study the color system determined by three color properties (Hue, Value and Chroma), without considering complex printing, and so on. For simplicity, each property of Hue, Value and Chroma is divided into three levels, i.e. low, middle and high. In this case, we obtain 9 color elements (Low Hue, Middle Hue, High Hue, Low Value, Middle Value, High Value, Low Chroma, Middle Chroma, High Chroma), which constitute 27 color combinations.

(c) Fabric

In our study, after discussion with fashion designers, we identify five sensory properties related to denim fabrics: “softness”, “roughness”, “wrinkle-resistance”, “warmness”, and “draping” for denim fabrics. They are represented by 5 semantically opposite keyword pairs: “soft-hard (sp_1) ”, “smooth-rough (sp_2) ”, “wrinkle resistance-crumply (sp_3) ”, “cool-warm” (sp_4) and “draped-non draped(sp_5)”, each with seven evaluation levels. The descriptions [89, 96] and the 7-points scales are shown as Table 2-7 and Figure 2-7 respectively.

Table 2-7 The descriptions of sensory properties of fabrics

Fabric sensory property	Description
Soft/	Not firm against pressure
Hard	Firm and stiff, not easily broken or bent
Smooth/	Having an even surface
Rough	Having an uneven surface
Wrinkle-Resistant/	Not likely to have wrinkles when grasped, folded or pressed
Crumply	Easy to have wrinkles when grasped, folded or pressed
Cool/	Not having a pleasant feeling of heat when touched
Warm	Having a pleasant feeling of heat when touched
Draped/	Easy to hang or stretch out loosely and carelessly
non-Draped	Difficult to hang or stretch out loosely and carelessly

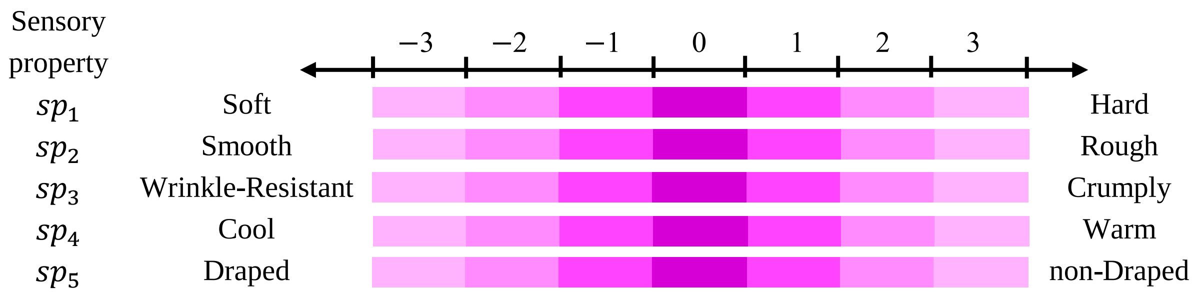


Figure 2-7 Semantic differential scales of sensory properties of fabrics

2.4.3 Related sensory experiments

We propose six sensory evaluation experiments (from Experiment 3 to 8) for acquiring the experts’ perception and their knowledge. (The panelists participated in various experiments are listed in Table 2-8). The details of these groups have been described in Section 2.4.1.

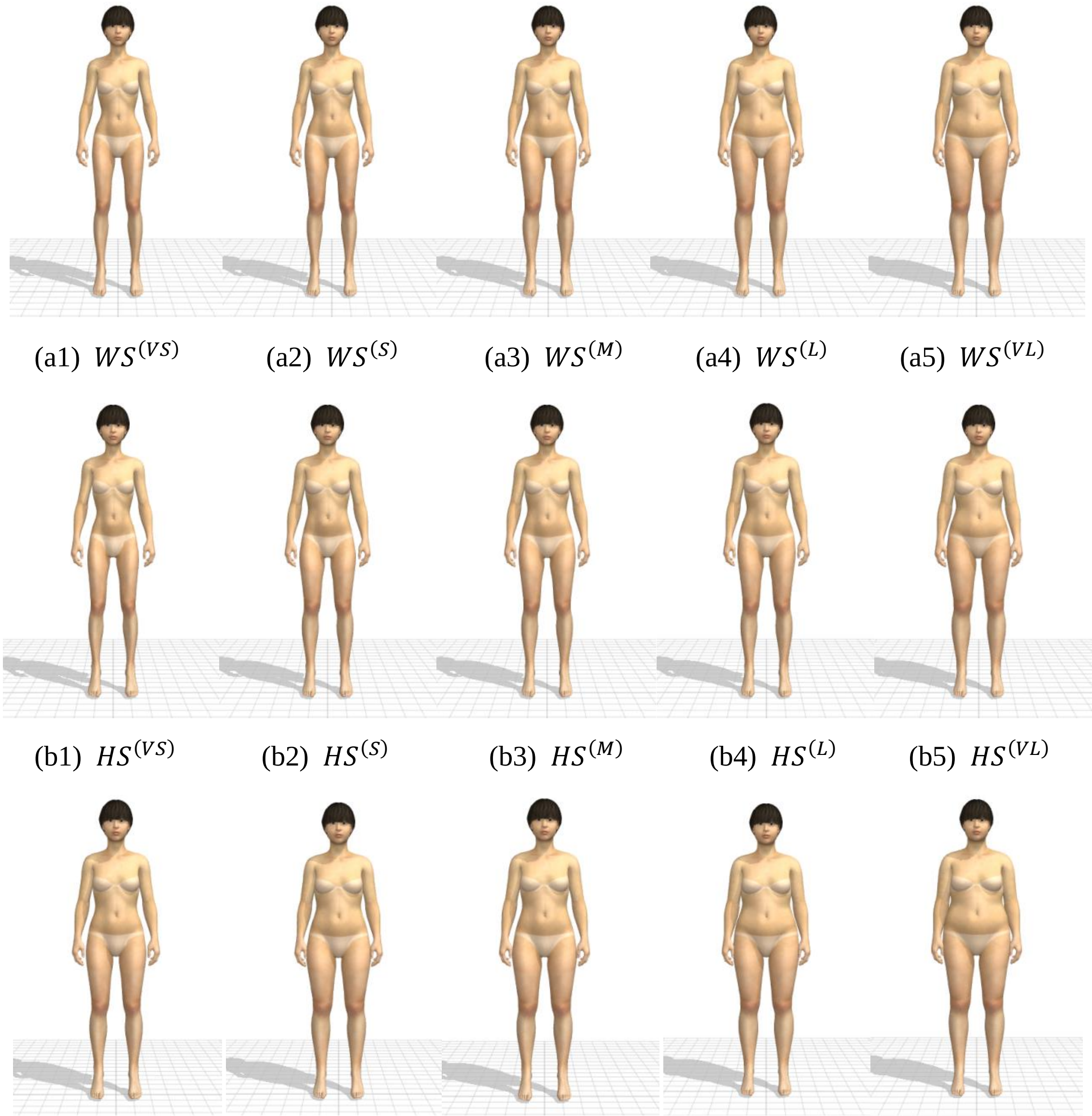
Table 2-8 The panelists in various experiments

Experiment No.	Experiment 3	Experiment 4~5	Experiment 6	Experiment 7	Experiment 8
Panel composition	Group 2	Group 1 Group 2	Group 1 Group 3	Group 3	All panelists

2.4.3.1 Evaluation experiment of different body position shapes (Experiment 3)

Six panelists in Group 2 are invited to perform this experiment. Before the experiment, the pictures of 3D virtual body shapes are first generated for the 118 subjects selected in Experiment 1 (body measurements). As the evaluation procedure is very time-consuming and easy to make people tired, we suggest each panelist to evaluate only one of six key lower body positions (e.g. Waist, Hip, Abdomen, Leg, Thigh and Calf).

During the experiment, each body position is classified into 5 sensory classes according to the visual perception on all the 118 3D human samples generated in Experiment 1 (See Section 2.1). The typical example graphs of various sensory classes with 160cm Stature (the standard stature in Chinese Nation Size Standard) are shown in Figure 2-8.



(a1) $WS^{(VS)}$ (a2) $WS^{(S)}$ (a3) $WS^{(M)}$ (a4) $WS^{(L)}$ (a5) $WS^{(VL)}$

(b1) $HS^{(VS)}$ (b2) $HS^{(S)}$ (b3) $HS^{(M)}$ (b4) $HS^{(L)}$ (b5) $HS^{(VL)}$

(c1) $AS^{(VS)}$ (c2) $AS^{(S)}$ (c3) $AS^{(M)}$ (c4) $AS^{(L)}$ (c5) $AS^{(VL)}$

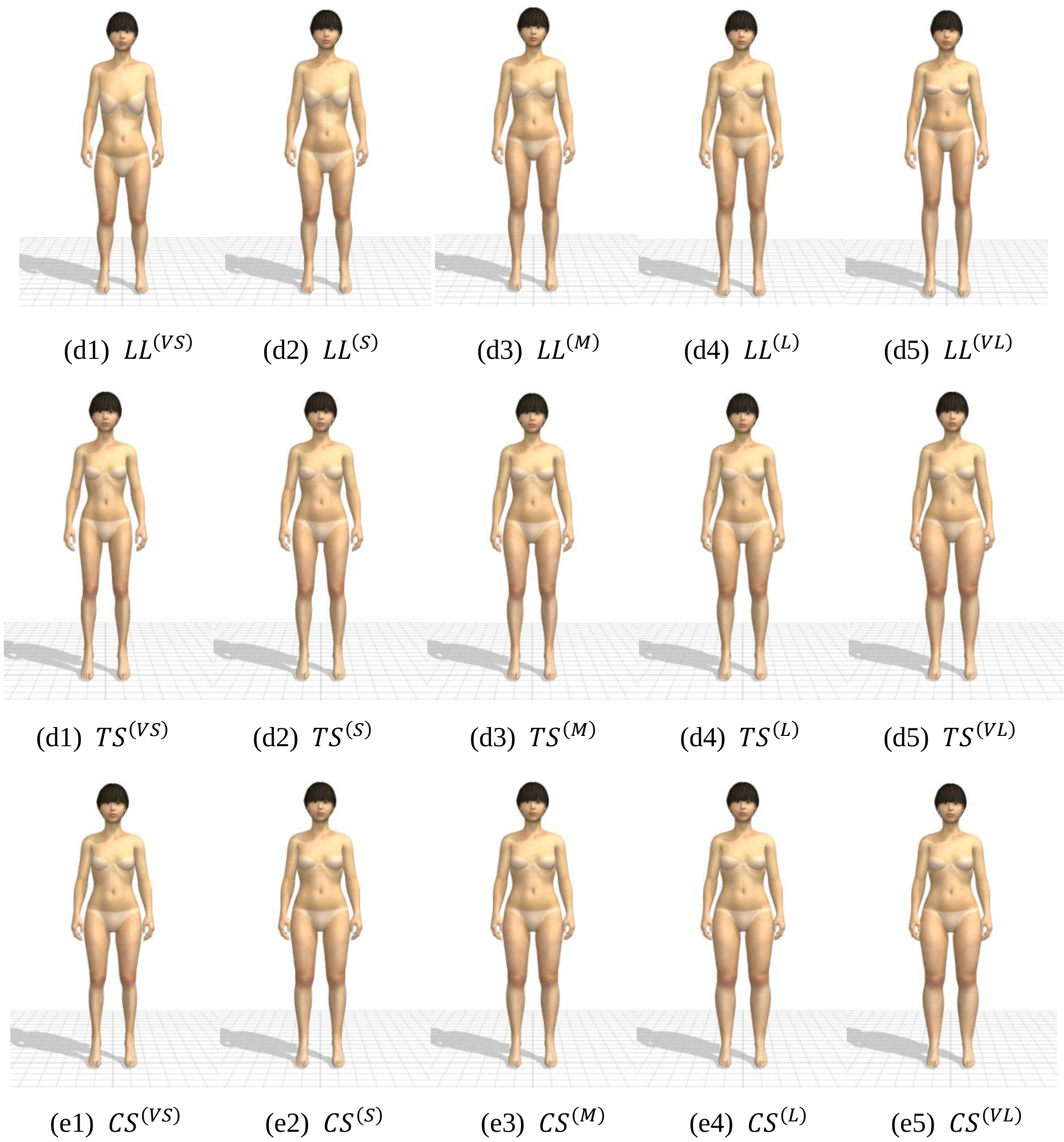


Figure 2-8 The typical example graphs of various sensory classes

In this way, each specific body shape belongs to one of the five sensory classes for each body position. These evaluation results (sensory body shape classification) will be combined with the body measurements-based classification (Experiment 1) for performing a more accurate and more significant design-oriented overall classification of body shapes.

2.4.3.2 Relationship between body shapes and basic style elements (Experiment 4)

The aim of this experiment is to characterize the relation between body shapes and basic design styles in the context of women jeans' design. The other style elements, i.e. details and accessories, are not strongly related to body shapes.

Twelve panelists in Group 1 and Group 2 are invited to perform this experiment. During this experiment, the panelists are asked to determine whether each style element is fit for the body positions of a specific body shape, and give the corresponding evaluation scores, selected from the set of {*unfit*, *neutral*, *fit*} according to the three-points. We denote *unfit*, *neutral*, *fit* by -1, 0, 1 respectively.

2.4.3.3 Relationship between fashion themes and style elements (Experiment 5)

The aim of this experiment is to characterize the relation between fashion themes and design styles. Twelve panelists in Group 1 and Group 2 are invited to perform this experiment. The results of this experiment are obtained by giving the intensity of the relation between each style element and each theme using the seven-points scale method.

2.4.3.4 Relationship between fashion themes and color elements (Experiment 6)

From the discussion of Chapter 1, we know that different colors can express different emotions. In fact, a fashion theme can be regarded as expression of a scenario or an ambiance. Therefore, we can directly find out the relation between fashion themes and color emotions with different Hue, Value and Chroma. The aim of this experiment is to characterize the relation fashion themes and color elements in the context of women's jeans design.

Nine panelists in Group 1 and Group 3 are invited to perform this experiment. During this experiment, for each color, each panelist is asked to give an evaluation score the closest to each fashion theme.

2.4.3.5 Sensory properties of fabrics (Experiment 7)

Three panelists in Group 3 perform the sensory evaluation of fabrics. Before the tests, all the fabric samples are conditioned for a minimum of 24 hours under the standard atmospheric condition (20±2℃ temperature and 65±2% relative humidity), and the panelists are asked to wash and dry their hands with non-moisturizing soup and paper towel provided [89].

During the experiment, all samples are laid on a clean big table in a laboratory under the above conditions. For each descriptor, the panelists are suggested to first select three typical fabrics (two extreme samples (e.g. the softest and the hardest) and one medium sample). Then, they compare the remaining fabric samples with these three typical samples and give them evaluations scores according to the seven-points scale. In the whole evaluation process, the panelists can achieve the tests by combining real touch (contact and grasping as Figure 2-9) and vision.


(a) contact


(b) grasping

Figure 2-9 real touch to fabric

2.4.3.6 Relationship between fashion themes and sensory properties of fabrics (Experiment 8)

This relationship means the extent to what one fabric is relevant to a specific fashion theme. In fact, the sensory properties describing fabrics, obtained in Experiment 7, are strongly related to the three fashion themes identified in Section 2.4.2.

All the fifteen panelists are invited to perform this experiment. During this experiment, for each fashion theme and each sensory property, both decomposed into 7 evaluation levels, each panelist is asked to evaluate, for each level of the sensory property, which level of the fashion theme is the most relevant. This evaluation is carried out with the references of the representative fabric samples and the image describing the related fashion theme. One example of evaluating the relation between the fashion theme "Elegant-Wild" and the sensory property "Soft-Hard" by one panelist is given below (The most relevant level of fashion theme to each level of "Soft-Hard" is represented by using " √ ").

Table 2-9 One example of evaluating the relation between the fashion theme and the sensory property

	extreme Elegant	Elegant	a little Elegant	neutral	a little Wild	Wild	extreme Wild
extreme Soft				√			
rather Soft				√			
a little Soft		√					
neutral			√				
a Little Hard					√		
rather Hard						√	
extreme Hard							√

In Table 2-9, we can find that the ambiance "rather elegant" can be enhanced if the fabric is a little soft and the level of "wild" can be increased with the level of fabric hardness. However, there is no influence on this fashion theme if the fabric becomes rather soft or extremely soft.

2.5 Mathematical Formalization of Involved Data

For realizing mathematical modeling and analysis, we formalize all involved data as follows.

2.5.1 Formalization on body shapes

Let $B = \{b_1, b_2, \dots, b_n\}$ be the set of n representative human bodies.

Let $BM = \{bm_1, bm_2, \dots, bm_p\}$ be the set of p key dimensions (measurements) of a human body.

Let $SI = \{si_1, si_2, \dots, si_q\}$ be the set of q body indices of a body shape, calculated from ratios and differences of anthropometric data in BM.

The q body indices in SI can be reorganized into 6 subsets each characterizing the shape of one specific body position (waist shape, hip shape, abdomen shape, leg length, thigh shape, calf shape). These six body positions are used for characterizing the low body shape and there are λ_i types of shapes for the i-th body position $(i = 1,2, \dots, 6)$.

Let $ws = \left(ws_1, ws_2, \dots, ws_{\lambda_1}\right)$ be the waist shape vector. It is is a λ_1-dimensional unit coordinate row vector, in which one element is 1 and the others 0. For a specific body shape, the corresponding waist shape vector ws can be calculated from the values of SI by using the algorithm of human body classification in Chapter 4.

According to the same idea, we define $hs = (hs_1, hs_2, \dots, hs_{\lambda_2})$ as the hip shape vector, $as = (as_1, as_2, \dots, as_{\lambda_3})$ as the abdomen shape vector, $ll = (ll_1, ll_2, \dots, ll_{\lambda_4})$ as the leg length vector, $ts = (ts_1, ts_2, \dots, ts_{\lambda_5})$ as the thigh shape vector, $cs = (cs_1, cs_2, \dots, cs_{\lambda_6})$ as the calf shape vector. These vectors can also be obtained by the classification algorithm in Chapter 4.

Denote $\lambda = \sum_{i=1}^{6} \lambda_i$ (the total number of lower body shapes obtained by combining all possible types of body positions).

Let a block matrix $BODY$ be the body shape matrix. Where

$$BODY = \begin{pmatrix} ws & 0 & 0 & 0 & 0 & 0 \\ 0 & hs & 0 & 0 & 0 & 0 \\ 0 & 0 & as & 0 & 0 & 0 \\ 0 & 0 & 0 & ll & 0 & 0 \\ 0 & 0 & 0 & 0 & ts & 0 \\ 0 & 0 & 0 & 0 & 0 & cs \end{pmatrix}_{6\times\lambda}$$

Let $bs = (i_1, i_2, i_3, i_4, i_5, i_6)$ be a specific lower body shape vector if $ws_{i_1} = hs_{i_2} =$

$as_{i_3} = ll_{i_4} = ts_{i_5} = cs_{i_6} = 1$, and all the lower body shape vectors constitute a set of Lower Body Shapes.

2.5.2 Formalization on garments

Let $PATTERN = \{PATTERN_1, PATTERN_2, \dots, PATTERN_{k_1}\}$ be the set of Pattern elements. As only one pattern is selected for each garment design (jeans), we propose to use a pattern vector, i.e. $pattern = (pattern_1, pattern_2, \dots, pattern_{k_1})$ in the following computation. We have

$$pattern_i = \begin{cases} 1, & \text{if the pattern } PATTERN_i \text{ is selected} \\ 0, & \text{otherwise} \end{cases} \qquad (i = 1,2,\dots,k_1)$$

Let $WAIST = \{WAIST_1, WAIST_2, \dots, WAIST_{k_2}\}$ be the set of Waist-Level elements. As only one waist-level is selected for each garment design, we propose to use a waist-level vector, i.e. $waist = (waist_1, waist_2, \dots, waist_{k_2})$ in the following computation. We have

$$waist_i = \begin{cases} 1, & \text{if the waist-level } WAIST_i \text{ is selected} \\ 0, & \text{otherwise} \end{cases} \qquad (i = 1,2,\dots,k_2)$$

Let $LEG = \{LEG_1, LEG_2, \dots, LEG_{k_3}\}$ be the set of Leg-Opening-Level elements. As only one leg-opening-level is selected for each garment design, we propose to use a leg-opening-level vector, i.e. $leg = (leg_1, leg_2, \dots, leg_{k_3})$ in the following computation. We have

$$leg_i = \begin{cases} 1, & \text{if the leg-opening-level } LEG_i \text{ is selected} \\ 0, & \text{otherwise} \end{cases} \qquad (i = 1,2,\dots,k_3)$$

Let BS be the set of all the basic style elements.

Let $s_1 = (PATTERN_x, WAIST_y, LEG_z)$ $(x \in \{1,\dots,k_1\},\ y \in \{1,\dots,k_2\},\ z \in \{1,\dots,k_3\})$ be a specific basic style vector. All basic style vectors constitute a set of Basic Styles S_1, obtained by combining all basic style components.

Let $DETAIL = \{DETAIL_1, DETAIL_2, \dots, DETAIL_{\mu_1}\}$ be the set of all the μ_1 detail components and there are n_i elements in each detail component $DETAIL_i$ $(i \in \{1,2,\dots,\mu_1\})$, denoted as $DETAIL_{i1}, DETAIL_{i2} \dots, DETAIL_{in_i}$ (Table 2-5). As only one element is selected for each detail component, we propose to use μ_1 detail component vectors, i.e. $d^{(i)} = (detail_{i1}, detail_{i2}, \dots, detail_{in_i})$ $(i = 1,2,\dots,\mu_1)$ in the following computation. We have

$$detail_{ij} = \begin{cases} 1, & \text{if the detail element } DETAIL_{ij} \text{ is selected} \\ 0, & \text{otherwise} \end{cases} \qquad (i = 1,2,\dots,\mu_1; j = 1,2,\dots,n_i)$$

Denote $k_4 = \sum_{i=1}^{\mu_1} n_i$ (the total number of all possible detail elements).

Let $ACCESSORY = \{ACCESSORY_0, ACCESSORY_1, ACCESSORY_2, \dots, ACCESSORY_{k_5}\}$ be the set of all the Accessories ("$ACCESSORY_0$" represents "no accessory"). As multiple accessories can be selected for each garment design, we propose to use an accessory vector, i.e. $accessory = (accessory_0, accessory_1, accessory_2, \dots, accessory_{k_5})$ in the following computation. We have

$$accessory_i = \begin{cases} 1, & \text{if the accessory } ACCESSORY_i \text{ is selected} \\ 0, & \text{otherwise} \end{cases} \qquad (i = 0,1,2, \dots, k_5)$$

Obviously, all the other elements of a equal to 0 if $a_0 = 1$.

We transform $accessory$ to the sum of μ_2 unit coordinate row vectors $a^{(i)}$ $(i = 1,2, \dots, \mu_2)$ if μ_2 accessories ($\mu_2 \leq k_5$) are selected (μ_2 can be alterable for different design schemes). Denote

$$a\mu_2 = \begin{pmatrix} a^{(1)} \\ a^{(2)} \\ \vdots \\ a^{(\mu_2)} \end{pmatrix}$$

Denote $K_1 = k_1 + k_2 + k_3$ (the total number of all possible basic design style elements), $K = k_1 + k_2 + k_3 + k_4 + k_5$ (the total number of all possible design style elements).

Let SE be the set of all the style elements.

Let $s = (PATTERN_x, WAIST_y, LEG_z, DETAIL_{1i_1}, \dots, DETAIL_{\mu_1 i_{\mu_1}}, ACCESSORY_{j_1}, \dots, ACCESSORY_{j_{\mu_2}})$ be a specific style vector, and all style vectors constitute a set of Design Styles S, obtained by combining all style components.

Denote $\mu = 3 + \mu_1 + \mu_2$ (the total number of all style elements in a specific design style).

Let a block matrix $STYLE$ be the style matrix. Where

$$STYLE = \begin{pmatrix} pattern & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & waist & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & leg & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & d^{(1)} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \ddots & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & d^{(\mu_1)} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & a\mu_2 \end{pmatrix}_{\mu \times K}$$

Let $T = \{T_1, T_2, \dots, T_t\}$ be the set of t fashion themes.

Let $HUE = \{HUE_1, HUE_2, \dots, HUE_{v_1}\}$ be the set of the Hue elements. As only one hue is selected for each garment color, we propose to use a hue vector, i.e. $hue = (hue_1, hue_2, \dots, hue_{v_1})$ in the following computation. We have

$$hue_i = \begin{cases} 1, & \text{if the hue element } HUE_i \text{ is selected} \\ 0, & \text{otherwise} \end{cases} \qquad (i = 1,2, \dots, v_1)$$

Let $VALUE = \{VALUE_1, VALUE_2, \dots, VALUE_{v_2}\}$ be the set of the value elements. As only one value is selected for each garment color, we propose to use a value vector, i.e. $value = (value_1, value_2, \dots, value_{v_1})$ in the following computation. We have

$$value_i = \begin{cases} 1, & \text{if the value element } VALUE_i \text{ is selected} \\ 0, & \text{otherwise} \end{cases} \qquad (i = 1,2,\dots,v_2)$$

Let $CHROMA = \{CHROMA_1, CHROMA_2, \dots, CHROMA_{v_3}\}$ be the set of the Chroma elements. As only one chroma is selected for each garment color, we propose to use a chroma vector, i.e. $chroma = (chroma_1, chroma_2, \dots, chroma_{v_3})$ in the following computation. We have

$$chroma_i = \begin{cases} 1, & \text{if the chroma element } CHROMA_i \text{ is selected} \\ 0, & \text{otherwise} \end{cases} \qquad (i = 1,2,\dots,v_3)$$

Let $c = (HUE_x, VALUE_y, CHROMA_z)$ be a specific color vector, and all color vectors constitute a set of Colors C, obtained by combining all color properties.

Denote $V = v_1 + v_2 + v_3$ (the total number of all possible garment color elements).

Let a block matrix $COLOR$ be the color matrix. Where

$$COLOR = \begin{pmatrix} hue & 0 & 0 \\ 0 & value & 0 \\ 0 & 0 & chroma \end{pmatrix}_{3\times V}$$

Let $F = \{f_1, f_2, \dots, f_m\}$ be the set of all the m representative fabrics.

Let $TP = \{tp_1, tp_2, \dots, tp_{u_1}\}$ be the set of all the u_1 technical parameters of fabrics.

The u_1 technical parameter values of all the m fabrics in F constitute a matrix, denoted as $\text{TPM} = (p_{ij})_{m\times u_1}$ with $i = 1, 2, \dots, m,\ j = 1, 2, \dots, u_1$.

Let $SP = \{sp_1, sp_2, \dots, sp_{u_2}\}$ be the set of all the u_2 sensory properties of fabrics.

The evaluation score of each sensory property of all the m fabrics in F is from a set of 7 levels according to the 7-points scale of the sensory property.

CHAPTER 3 COMPUTATIONAL AND MODELING TOOLS

In this Chapter, we will present the relevant computational and modeling tools used in the proposed garment design recommendation system. More emphasis will be put on the basic principles and application contexts of the used soft computing tools, including fuzzy technique, rough set method and Genetic Algorithms (GA). Some well-known statistical methods, such as outlier examination, various distribution test, hypothesis tests, have also been used in our study but are not discussed here. Also, we will shortly explain how these computational tools are applied in the proposed models and system. The details of the applications will be provided in Chapter 4 and Chapter 5.

3.1 Fuzzy Theory and Related Technique

Early in 1965, Professor L. A. Zadeh, the cybernetics expert from University of California, published a pioneering paper "*Fuzzy Sets*" in *Information & cybernetics* [97]. This marks the starting of Fuzzy Mathematics. Since then, fuzzy theories and techniques have rapidly been developed and applied in various fields.

Both fuzzy theory and technique are based on Fuzzy Sets, which are the foundation of the entire fuzzy systems technology, including fuzzy systems modeling, fuzzy decision-making, fuzzy information processing, fuzzy control, and fuzzy management, and so on.

3.1.1 Related notions of Fuzzy sets

The classical sets theory is built on the fundamental concept of set of which an individual is either a member or not a member. It is not allowed an entity is in a set and in another set at the same time. On the contrary, fuzzy set theory accepts partial memberships.

3.1.1.1 Fuzzy set and fuzzy membership function

A fuzzy set consists of two components: a set and a membership function defined on the set, different from the classical set theory.

Definition 3-1 [62] Let U be the universe, a *fuzzy subset* $\tilde{A}$ on U is defined by the following mapping $\mu_{\tilde{A}}$.

$$\mu_{\tilde{A}}:\ U \to [0,1]$$
$$x \longmapsto \mu_{\tilde{A}}(x) \in [0,1]$$

$\mu_{\tilde{A}}$ is called the *Membership Function* of $\tilde{A}$, and $\mu_{\tilde{A}}(x)$ (denoted as $\tilde{A}(x)$ for convenience) is called the *Membership* of x to $\tilde{A}$. The set of all fuzzy subset on U is called *fuzzy power set* of U, and denoted as $\mathcal{F}(U)$.

Obviously, the fuzzy subset $\tilde{A}$ becomes a classical set if $\mu_{\tilde{A}}(x) \in \{0, 1\}$ and $\mu_{\tilde{A}}$ is the characteristic function.

In general, a fuzzy membership function can have various shapes (Figure 3-2), depending on the concerned application, and can be identified by different methods, such as fuzzy statistical method, assignment method by using existing fuzzy distribution.

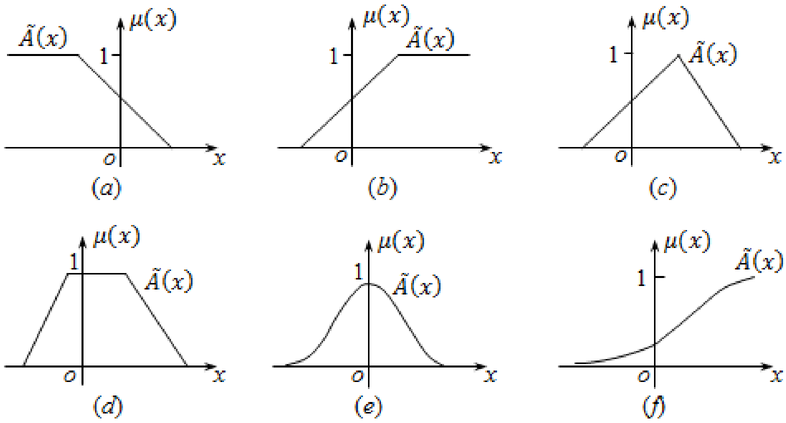


Figure 3-1 Some typical membership functions

3.1.1.2 Representation of Fuzzy sets

Let $U = \{x_1, x_2, \ldots, x_n\}$ be a finite universe and the membership function of x_i to the fuzzy set $\tilde{A}$ be $\tilde{A}(x_i)$ $(i = 1,2,\ldots,n)$. The fuzzy set $\tilde{A}$ can be represented by two typical methods.

(1) Zadeh expression: $\tilde{A} = \frac{\tilde{A}(x_1)}{x_1} + \frac{\tilde{A}(x_2)}{x_2} + \cdots + \frac{\tilde{A}(x_n)}{x_n}$;

(2) Vector expression: $\tilde{A} = (\tilde{A}(x_1), \tilde{A}(x_2), \ldots, \tilde{A}(x_n))$.

3.1.2 Basic operations of fuzzy sets

The operations of fuzzy sets are defined by relations between membership functions of fuzzy sets. They include Inclusion, Equality, Union, Intersection and Complement.

Suppose $\tilde{A}, \tilde{B} \in \mathcal{F}(U)$, the operations of $\tilde{A}$ and $\tilde{B}$ are defined by their membership functions.

(1) Inclusion: $\tilde{A} \subseteq \tilde{B} \Leftrightarrow \tilde{A}(x) \leq \tilde{B}(x), \forall\, x \in U$

(2) Equivalence: $\tilde{A} = \tilde{B} \Leftrightarrow \tilde{A}(x) = \tilde{B}(x), \forall\, x \in U$

(3) Union: $\left(\tilde{A} \cup \tilde{B}\right)(x) = \tilde{A}(x) \vee \tilde{B}(x), \quad \forall \in U$

(4) Intersection: $\left(\tilde{A} \cap \tilde{B}\right)(x) = \tilde{A}(x) \wedge \tilde{B}(x), \quad \forall\, x \in U$

(5) Complement: $\tilde{A}^C(x) = 1 - \tilde{A}(x), \quad \forall\, x \in U$

The schematic diagram of Union, Intersection and Complement are shown in Figure 3-2.

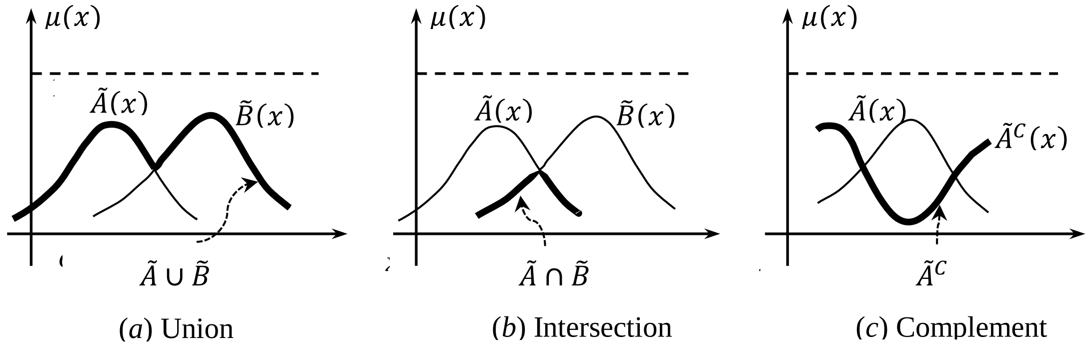


Figure 3-2 The schematic diagram of fuzzy operations (the place with bold line)

3.1.3 Fuzzy Matrix

Definition 3-2 [62] The matrix $\boldsymbol{R} = (r_{ij})_{m \times n}$ is called *fuzzy matrix* if $r_{ij} \in [0, 1]$, $\forall\, i \in \{1, 2, \dots, m\}$; $j \in \{1, 2, \dots, n\}$. Especially, $\boldsymbol{R}$ is a fuzzy vector if $m = 1$.

Definition 3-3 [62] Let $\boldsymbol{A} = (a_{ij})_{m \times s}$, $\boldsymbol{B} = (b_{ij})_{s \times n}$ be two fuzzy matrices. The *max-min composition operation* of $\boldsymbol{A}$ and $\boldsymbol{B}$ is defined by

$$\boldsymbol{A} \circ \boldsymbol{B} = \left(c_{ij}\right)_{m \times n} \qquad \left(c_{ij} = \bigvee_{k=1}^{s} \left(a_{ik} \wedge b_{kj}\right)\right) \tag{3-1}$$

In practice, we can define the composition operation by other methods.

3.1.4 Fuzzy Relation

Definition 3-4 [62] Let U, V be two universes, a fuzzy subset $\tilde{R}$ on $U \times V$ is defined as the *fuzzy relation* from U to V, and denoted by $U \xrightarrow{\tilde{R}} V$. The membership function of $\tilde{R}$ is defined by

$$\mu_{\tilde{R}}:\ U \times V \to [0, 1]$$
$$(x, y) \longmapsto \mu_{\tilde{R}}(x, y) \in [0, 1]$$

The membership $\mu_{\tilde{R}}(x, y)$, denoted by $\tilde{R}(x, y)$, is also called the relevancy of the fuzzy relation $\tilde{R}$.

If $U=\{x_1,x_2,\dots,x_m\}$, $V=\{y_1,y_2,\dots,y_n\}$ are finite universes, the fuzzy relation $\tilde{R}$ can be expressed by a fuzzy matrix $\boldsymbol{R}=(\tilde{R}(x,y))_{m\times n}$.

Definition 3-5 [62] Let U, V, W be three universes, and let $\tilde{R}_1$ be the fuzzy relation from U to V and $\tilde{R}_2$ be the fuzzy relation from V to W. The *Composition* $\tilde{R}_1\circ\tilde{R}_2$ of $\tilde{R}_1$ and $\tilde{R}_2$ is defined by a fuzzy relation from U to W, and its membership function is defined as follows.

$$\tilde{R}_1\circ\tilde{R}_2(u,w)=\bigvee_{v\in V}\left(\tilde{R}_1(u,v)\wedge\tilde{R}_2(v,w)\right) \tag{3-2}$$

3.1.5 Fuzzy Model Recognition

Model Recognition is to recognize and classify a research object according to its features. By Model Recognition, we can identify which model should be affected to a specific object if a number of standard models (called standard models base) are available..

Model recognition is called Fuzzy Model Recognition if several standard models can be affected to a specific object. . In fuzzy model recognition, the following three categories of methods are generally utilized.

3.1.5.1 Fuzzy model recognition: the first category [62]

The purpose of this method is to recognize if a single object can be affected to a fuzzy model.

Let $\tilde{A}_1,\tilde{A}_2,\dots,\tilde{A}_m$ be m fuzzy sets (models) defined on the universe $U=\{x_1,x_2,\dots,x_n\}$, which constitute a standard models base, and $\tilde{A}$ be a standard model defined on U.

(1) Maximal Membership Principle Ⅰ:

$\forall\, x\in U$, The object x is affected to $\tilde{A}_{i_0}$ if $\exists\ i_0\in\{1,2,\dots,m\}$, s.t.

$$\tilde{A}_{i_0}(x)=\bigvee_{k=1}^{m}\tilde{A}_k(x) \tag{3-3}$$

(2) Maximal Membership Principle Ⅱ:

Assuming that $x_1,x_2,\dots,x_n$ $(\in U)$ are n objected to be identified, the object x_k will be selected,

if $\exists\ x_k\in U$, s.t.

$$\tilde{A}(x_k)=\bigvee_{i=1}^{n}\tilde{A}(x_i) \tag{3-4}$$

(3) Threshold Principle Ⅰ:

$\forall\, x\in U$ and a threshold $\alpha\in[0,1]$. x is the relative member of $\bigcap_{j=1}^{k}\tilde{A}_{i_j}$ if and only if

$\exists\ i_1, i_2, \dots, i_k \in \{1, 2, \dots, m\}$, s.t. $\tilde{A}_{i_j}(x) \geq \alpha\ (j = 1, 2, \dots, k)$.

(4) Threshold Principle Ⅱ :

$\forall\ x \in U.\ x$ is the relative member of $\tilde{A}$ if and only if $\tilde{A}(x) \geq \alpha$.

3.1.5.2 Fuzzy model recognition: the second category [62]

The purpose of this method is to recognize the relevance of a fuzzy set to a standard fuzzy model. It depends on the close degree between two fuzzy sets.

Definition 3-6 Let $\tilde{A}, \tilde{B} \in \mathcal{F}(U)$. Given a mapping

$$\sigma: \mathcal{F}(U) \times \mathcal{F}(U) \to [0, 1]$$
$$(\tilde{A}, \tilde{B}) \mapsto \sigma(\tilde{A}, \tilde{B}) \in [0, 1]$$

$\sigma(\tilde{A}, \tilde{B})$ is defined the *Close Degree between fuzzy sets* $\tilde{A}$ and $\tilde{B}$ if σ satisfies the following condition.

a) $0 \leq \sigma(\tilde{A}, \tilde{B}) \leq 1,\ \sigma(U, \emptyset) = 0,\ \sigma(\tilde{A}, \tilde{B}) = 1$ if and only if $\tilde{A} = \tilde{B}$.

b) $\sigma(\tilde{A}, \tilde{B}) = \sigma(\tilde{B}, \tilde{A})$.

c) $\sigma(\tilde{A}, \tilde{C}) \subseteq \sigma(\tilde{A}, \tilde{B}) \wedge \sigma(B, \tilde{C})$ if $\tilde{A} \subseteq \tilde{B} \subseteq \tilde{C}$.

The larger the Close Degree between fuzzy sets $\tilde{A}$ and $\tilde{B}$ is, the closer $\tilde{A}$ is to $\tilde{B}$.

According to this definition, researchers gave many computational formulas [98, 99]. Based on the Close Degree between fuzzy sets, the concepts of the model recognition are defined as follows.

(1) Fuzzy Selecting Near Principle of single attribute

Assuming that m fuzzy sets $\tilde{A}_1, \tilde{A}_2, \dots, \tilde{A}_m$ on the universe U constitute a standard models base and $\tilde{B} \in \mathcal{F}(U)$ is a model to be identified.

$\tilde{B}$ is the closest to $\tilde{A}_{i_0}$ if $\exists\ i_0 \in \{1, 2, \dots, m\}$, s.t.

$$\sigma(\tilde{A}_{i_0}, \tilde{B}) = \bigvee_{k=1}^{m} \sigma(\tilde{A}_k, \tilde{B}) \qquad (3\text{-}5)$$

(2) Fuzzy Selecting Near Principle of multiple attributes

Let m fuzzy sets $\tilde{A}_1, \tilde{A}_2, \dots, \tilde{A}_m$ on the universe U constitute a standard models base. Each model $\tilde{A}_i$ is described by n attributes, i.e.

$$\tilde{A}_i = (\tilde{A}_{i1}, \tilde{A}_{i2}, \dots, \tilde{A}_{in}) \qquad (i = 1, 2, \dots, m)$$

Let $\tilde{B} = (\tilde{B}_1, \tilde{B}_2, \dots, \tilde{B}_n)$ be a model to be identified, where $\tilde{B}_j \in \mathcal{F}(U)$. Denote

$$s_i = \bigwedge_{j=1}^{n} \sigma(\tilde{A}_{ij}, \tilde{B}_j) \qquad (i = 1, 2, \dots, m) \qquad (3\text{-}6)$$

$\tilde{B}$ is closest to the class of $\tilde{A}_{i_0}$ if $\exists\ i_0 \in \{1, 2, \dots, m\}$, s.t.

$$s_{i_0} = \bigvee_{i=1}^{m} s_i \tag{3-7}$$

Example: The fuzzy recognition on the tea categories

Let the universe $U = \{\text{tea}\}$, and the quality indices of teas include Shape (x_1), Color (x_2), Aroma (x_3) and Taste (x_4). The teas are requested to be classified as 3 categories from, which constitute the standard model base $\{\tilde{A}_1, \tilde{A}_2, \tilde{A}_3\}$ (three standard teas) on U.

$$\tilde{A}_1 = \frac{1}{x_1} + \frac{0.9}{x_2} + \frac{1}{x_3} + \frac{1}{x_4},\quad \tilde{A}_2 = \frac{0.6}{x_1} + \frac{0.5}{x_2} + \frac{0.7}{x_3} + \frac{0.7}{x_4},\quad \tilde{A}_3 = \frac{0.3}{x_1} + \frac{0.2}{x_2} + \frac{0.3}{x_3} + \frac{0.3}{x_4}.$$

$\tilde{B} = \frac{0.8}{S} + \frac{0.8}{C} + \frac{0.7}{A} + \frac{0.6}{T}$ is the object to be identified.

We compute the close degree by using the following formula [98, 99]].

$$\sigma(\tilde{A}, \tilde{B}) = \frac{\sum_{i=1}^{4}[\tilde{A}(x_i) \wedge \tilde{B}(x_i)]}{\sum_{i=1}^{4}[\tilde{A}(x_i) \vee \tilde{B}(x_i)]} \tag{3-8}$$

We have $\sigma(\tilde{A}_1, \tilde{B}) = 0.7346$, $\sigma(\tilde{A}_2, \tilde{B}) = 0.8000$, $\sigma(\tilde{A}_3, \tilde{B}) = 0.3793$.

$\sigma(\tilde{A}_2, \tilde{B}) = \bigvee_{k=1}^{3} \sigma(\tilde{A}_k, \tilde{B})$. According to Fuzzy Selecting Near Principle, the tea $\tilde{B}$ to be identified should be classified into the second category ($\tilde{A}_2$).

3.1.6 Fuzzy comprehensive evaluation [62]

Fuzzy comprehensive evaluation is an effective method to evaluate objects affected by multiple factors criteria, also called fuzzy multi-criteria decision making problem.

Let $U = \{u_1, u_2, \dots, u_n\}$ be n criteria, and $V = \{v_1, v_2, \dots, v_m\}$ be m evaluation grades.

Let the comprehensive evaluation result be the fuzzy set $\tilde{E} = (e_1\ e_2\ \dots\ e_m)$ on V, where e_j $(j = 1, 2, \dots, m)$ is the membership degree of the j-th evaluation grade v_j to $\tilde{E}$, i.e. $e_j = \tilde{E}(v_j)$.

The comprehensive evaluation result $\tilde{E}$ relies on the weights of various criteria, which constitute a fuzzy set $\tilde{W} = (w_1\ w_2\ \dots\ w_n) \in \mathcal{F}(U)$ with $\sum_{i=1}^{n} w_i = 1$, called weight vector. w_i is the weight of the i-th criterion.

3.1.6.1 The mathematical model of fuzzy comprehensive evaluation [62]

Step 1: Identifying the set of criteria $U = \{u_1, u_2, \dots, u_n\}$.

Step 2: Identifying the set of evaluation grades $V = \{v_1, v_2, \dots, v_m\}$.

Step 3: Single criterion fuzzy judgment

For each u_i, the evaluation result is $\tilde{f}(u_i)$. $\tilde{f}$ is a fuzzy mapping from U to V.

$$\tilde{f}:\ U \rightarrow \mathcal{F}(V)$$

$$u_i \longmapsto \tilde{f}(u_i) = (r_{i1}, r_{i2}, \dots, r_{im}) \in \mathcal{F}(V)$$

The fuzzy mapping can induce a fuzzy relation $\tilde{R}_f \in \mathcal{F}(U \times V)$, which satisfies

$$\tilde{R}_f((u_i, v_j) = \tilde{f}(u_i)(v_j) = r_{ij} \quad (i = 1, 2, \dots, n; j = 1, 2, \dots, m)$$

The fuzzy relation can be expressed by a fuzzy matrix $\boldsymbol{R}$ (called single criteron fuzzy judgment matrix) with

$$\boldsymbol{R} = \begin{pmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nm} \end{pmatrix} \tag{3-9}$$

Step 4: Fuzzy comprehensive evaluation

Given the weight vector $\boldsymbol{W} = (w_1\ w_2\ \dots\ w_n)$, we obtain the comprehensive evaluation decision as follows.

$$\tilde{E} = \boldsymbol{W} \circ \boldsymbol{R} \tag{3-10}$$

Example: The satisfaction evaluation of a type of jeans.

Assuming that we have a set of criteria $U = \{u_1, u_2, u_3\}$, where u_1, u_2, u_3 represent "color", "style" and "fabric quality" respectively, and the weight vector of criteria is $\boldsymbol{W} = (0.1, 0.5, 0.4)$. Assuming that the set of grades $V = \{v_1, v_2, v_3\}$, where v_1, v_2, v_3 represent "very satisfied", "not very satisfied" and "unsatisfied".

According to the experts' evaluations on the various criteria of the jeans, we obtain the evaluation matrix below.

$$\begin{pmatrix} 0.2 & 0.5 & 0.3 \\ 0.7 & 0.2 & 0.1 \\ 0.2 & 0.2 & 0.6 \end{pmatrix}$$

Thus, $\tilde{E} = \boldsymbol{W} \circ \boldsymbol{R} = (0.5, 0{,}2, 0.4)$, whose normalized form is $(0.46, 0.18, 0.36)$. Therefore, according to the Maximal Membership Principle, the ultimate evaluation of the jeans is "very satisfied".

3.1.6.2 Identification of the weights

There are many methods for identifying the relevant weights of the evaluation criteria. These methods include Frequency Statistics [62], Analytic Hierarchy Process (AHP) [62], Fuzzy relation Equation [62], etc. In our research, AHP is considered as a suitable method for identify the weights due to the relevancy of its qualitative comparisons between different criteria to acquired sensory data.

3.2 Rough Set Theory

The rough set theory was firstly proposed by Pawlak in 1980s for the study of intelligent systems characterized by inexact, uncertain or vague information [ref]. Since then, it has been demonstrated to be efficient in the fields of pattern recognition, decision support system, data mining, and become one of the key techniques in the area of soft computing.

A target or concept cannot be defined clearly if we have no enough knowledge. However, we can use a pair of classical sets defined in rough set theory to describe the concept roughly. The main difference between rough set theory and other mathematical tools for dealing with uncertain problems is that it doesn't need any prior information beyond the problem itself. The main goal of rough set analysis is to synthesize approximations of concepts from the acquired data.

3.2.1 Related notions of rough set

Definition 3-7 [100] Let an non-empty set U be the universe and $\boldsymbol{R}$ a family of the equivalence relations on U (denoted by U/R). The pair $K = (U, \boldsymbol{R})$ is a *Knowledge Base*.

$\forall\, R \subseteq R$, U/R presents the family of all equivalence classes in terms of the equivalence relation R (or classification of U in terms of R). Such family of equivalence classes is also referred to *concepts* of R. $\forall\, x \subseteq U$, $[x]_R$ is used to denote an equivalence class containing *x*.

Definition 3-8 [100] Let an non-empty set $P \subseteq \boldsymbol{R}$. $\cap P$ (the interSection of all equivalence relations in P) is also an equivalence, and will be denoted by $IND(P)$, it is referred to an *Indiscernibility Relation* over P in Pawlak's rough set theory.

$\forall\, P \subseteq \boldsymbol{R}$, $U/IND(P)$ is the family of all equivalence classes in terms of the set of equivalence relations P, each element in $U/IND(P)$ is referred to as as a *P*-basic knowledge, $[x]_P = \{y \in U: (x, y) \in IND(P)\}$ is the equivalence class of P, which contains x.

$\forall\, X \subseteq U$, if X is the union of some P-basic knowledge, X is P-definable; otherwise, X is P-undefinable. To describe the P-undefinable set more clearly, Pawlak proposed a rough set model as Definiton 3-9.

Definition 3-9 [100] Let $K = (U, \boldsymbol{R})$ be a Knowledge Base, $P \subseteq \boldsymbol{R}$. $\forall\, X \subseteq U$, the *Lower Approximation* $\underline{P}(X)$ and *Upper Approximation* $\overline{P}(X)$ of X are defined respectively as follows.

$$\underline{P}(X) = \{x \in U: [x]_P \subseteq X\} \tag{3-11}$$

$$= \bigcup\{Y \in U/IND(P): Y \subseteq X\} \tag{3-12}$$

$$\overline{P}(X) = \{x \in U: [x]_P \cap X \neq \emptyset\} \tag{3-13}$$

$$= \bigcup\{Y \in U/IND(P): Y \cap X \neq \emptyset\} \tag{3-14}$$

By Definition 3-11, we can see that two different approaches have been employed for the constructing of lower and upper approximations. The first one is a point-based approach (Equation (3-11) and Equation (3-13)), while the second one is a set-based approach (Equation (3-12) and Equation (3-14)).

In the point-based approach, the lower approximation is the set of elements, which can be certainly classified as elements of X; the upper approximation is the set of element, which can be possibly classified as elements of X.

In the set-based approach, the lower approximation is the union of some equivalence classes, which can be certainly classified as part of X; the upper approximation is the union of some equivalence classes, which can be possibly classified as part of X.

Definition 3-10 [100] Let $K = (U, \boldsymbol{R})$ be a Knowledge Base, $P \subseteq \boldsymbol{R}$. $\forall\, X \subseteq U$,

a) P-positive region of X is defined as $POS_P(X) = \underline{P}(X)$;

b) P-negative region of X is defined as $NEG_P(X) = U - \overline{P}(X)$;

c) P-boundary region of X is defined as $BN_P(X) = \overline{P}(X) - \underline{P}(X)$.

X is called as *Pawlak rough set* in terms of the indiscernibility relation $IND(P)$ if $BN_P(X) \neq \emptyset$ ($\overline{P}(X) \neq \underline{P}(X)$). Otherwise, X is called *Pawlak exact set* in terms of the indiscernibility relation $IND(P)$ if $BN_P(X) = \emptyset$ ($\overline{P}(X) = \underline{P}(X)$).

The schematic diagram of the concepts can be shown in Figure 3-5.

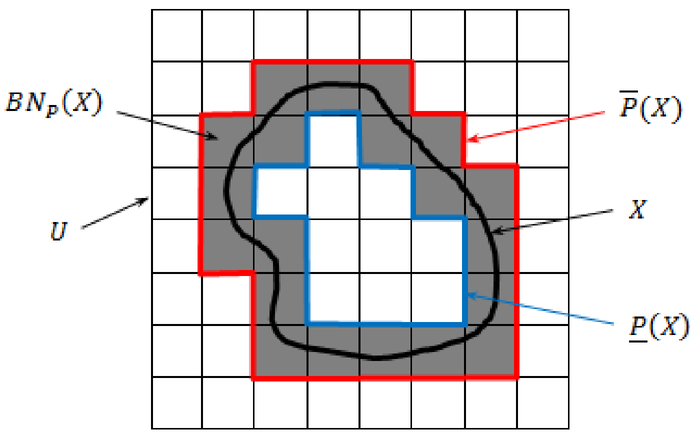


Figure 3-3 Lower Approximation and Upper Approximation of a rough set

3.2.2 Knowledge Reduction

Knowledge reduction is an important aspect of the rough set theory. It involves the research for particular subsets of the relations, which provide the same information for classification or some purposes as all of the relations in *R*. Such subsets are called as Reducts. The approach to find such subsets is knowledge reduction while the obtained subset is Reduct. Obviously, different requirements may induce different reducts.

3.2.2.1 Reduct of indiscernibility relation

Definition 3-11 [101] Let $K=(U,\boldsymbol{R})$ be a Knowledge Base. $\forall R\in\boldsymbol{R}$,

a) R is called as dispensable in $\boldsymbol{R}$ if $IND(\boldsymbol{R})=IND(\boldsymbol{R}-\{R\})$; otherwise, R is called indispensable in $\boldsymbol{R}$.

b) The family of the equivalence relations $\boldsymbol{R}$ is called as independent if each $R\in\boldsymbol{R}$ is indispensable in $\boldsymbol{R}$; otherwise, $\boldsymbol{R}$ is dependent.

Definition 3-12 [101] Let $K=(U,\boldsymbol{R})$ be a Knowledge Base, $Q\subseteq P\subseteq\boldsymbol{R}$.

c) Q is called as a *reduc*t of P if $IND(Q)=IND(P)$ and Q is independent.

d) The set of all indispensable relations in P is called the *core* of P and denoted by $CORE(P)$.

3.2.2.2 Reduct of positive region

Definition 3-13 [101] Let $K=(U,\boldsymbol{R})$ be a Knowledge Base, $Q\subseteq\boldsymbol{R}$, $S\subseteq P\subseteq\boldsymbol{R}$. If

$U/IND(Q)=\{X_1,X_2,\dots,X_m\}$, the positive region of Q in terms of P is defined by

$$POS_P(Q)=\bigcup_{i=1}^{m}\underline{P}(X_i) \tag{3-15}$$

a) R is called Q-dispensable in P if $POS_P(Q)=POS_{P-\{R\}}(Q)$ with $\forall R\in P$; otherwise, R is Q-indispensable in P.

b) P is called Q-dispendent in P if each R in P is Q-indispensable.

c) $S\subseteq P$ is called Q-reduct of P if $POS_P(Q)=POS_S(Q)$ and S is Q-dispendent.

d) The set of all Q-indispensable relations in P is called as the Q-*core* of P and is denoted by $CORE_Q(P)$.

Example: Assuming that $U=\{x_1,x_2,x_3,x_4,x_5\}$.

$U/IND(Q)=\{\{x_1,x_2\},\{x_3\},\{x_4,x_5\}\}=\{X_1,X_2,X_3\}$,

$U/IND(P)=\{\{x_1\},\{x_2,x_3\},\{x_4,x_5\}\}$.

Then, $P(X_1)=\{x_1\}$, $P(X_2)=\emptyset$, $P(X_3)=\{x_4,x_5\}$. Thus, $POS_P(Q)=\{x_1,x_4,x_5\}$.

3.2.3 Complete information system

3.2.3.1 Basic concepts

Since knowledge is understood as classification, which can be viewed as a semantic definition of knowledge in Pawlak's rough set theory, he employed a table of knowledge, which can represent equivalence relations in symbolic form for computer processing. This table is called *Knowledge Representation System* or *Information System*.

Definition 3-14 [102] Let U be the universe and AT the set of attributes. $\forall\, a \in AT$, V_a is the domain of a and V the domain of all attributes, i.e. $V = \bigcup_{a \in AT} V_a$. f is the information function such that $f(x,a) \in V_a$ with $x \in U$ and $a \in AT$. $I = (U, AT, V, f)$ is called an information system.

Evidently, the information system can be used to express the knowledge in $K = (U, \boldsymbol{R})$. Each attribute in I corresponds to an equivalence relation in K while $\forall\, R \in \boldsymbol{R}$, R corresponds to an attribute in I.

A complete information system indicates that all objects have deterministic values on every attribute. Therefore, given a knowledge base, we can construct a complete information system, in which each column corresponds to an equivalence relation in such knowledge base. The indiscernibility relation is then the classification analysis of all the attributes in such complete information system.

For an information system I, the relationships between objects can be described through their attributes values. With respect to a subset of attributes such that $A \subseteq AT$, an indiscernibility relation $IND(A)$ may be defined by

$$IND(A) = \{(x,y) \in U \times U : f(x,a) = f(y,a), \forall\, x \in A\} \qquad (3\text{-}16)$$

In fact, the information system with decision is more significant, which is just the decision system.

Definition 3-15 [102] $I = (U, AT \cup D, V, f, G, g)$ is called a decision system, in which AT is referred to as the set of condition attributes while D is the set of decision attributes and $AT \cap D = \emptyset$. $\forall\, d \in D$, G_d is the domain of d and G is the domain of all decision attributes, i.e. $G = \bigcup_{d \in D} G_d$. g is a decision function such that $g(x,d) \in G_d$ with $x \in U$ and $d \in D$.

Definition 3-16 [102] Let $I = (U, AT \cup D, V, f, g)$ be a decision system, I is called consistent decision system if $IND(AT) \subseteq IND(D)$; otherwise, it is inconsistent decision system.

3.2.3.2 Reduct of complete information system

We can get all reducts by using the discernibility matrix.

Definition 3-18 [102] Let $I = (U, AT, V, f)$ be an information system, $R_{AT} \in \boldsymbol{R}$. Suppose that

$$U/IND(R_{AT}) = \{C_i : 1 \le i \le t\}$$

Let $f_l(C_i)$ be the attribute value of attribute a_l on C_i. The discernibility attributes set between C_i and C_j is define by

$$D(C_i, C_j) = \{a_l \in A: f_l(C_i \neq f_l(C_j)\} \quad (3\text{-}17)$$

$\boldsymbol{D} = \left(D(C_i, C_j)\right)$ is called the discernibility matrix in I.

All reducts of I can be given by the following identification formula.

$$M = \bigwedge_{i \neq j}\left(\bigvee D(C_i, C_j)\right) = \bigvee_{k=1}^{p}\left(\bigwedge_{l=1}^{q_k} a_{i_l}\right) \quad (3\text{-}18)$$

Definition 3-19 [102] Let $I = (U, AT \cup D, V, f, G, g)$ be a consistent decision system. Let $g_d(C_i)$ be the attribute value of decision attribute d on C_i. The discernibility attributes set between C_i and C_j on decision attribute d is define by

$$D_d(C_i, C_j) = \begin{cases} \{a_l \in A: f_l(C_i) \neq f_l(C_j)\}, & g_d(C_i) \neq g_d(C_j) \\ A, & g_d(C_i) = g_d(C_j) \end{cases} \quad (3\text{-}19)$$

$\boldsymbol{D}_d = \left(D(C_i, C_j)\right)$ is called the discernibility matrix of consistent decision system.

All reducts of consistent decision system can be given by the following identification formula.

$$M = \bigwedge_{i \neq j}\left(\bigvee D_d(C_i, C_j)\right) = \bigvee_{k=1}^{p}\left(\bigwedge_{l=1}^{q_k} a_{i_l}\right) \quad (3\text{-}20)$$

For inconsistent decision system, we will not describe since it is very complex.

3.2.4 Incomplete information system [103]

An incomplete information system indicates an information system with unknown values [100].

At present, two strategies have been used in rough set theory to process incomplete information system. The first one is to transform an incomplete information system into a complete information system. The second one is to extend the classical rough set model by relaxing the requirement of indiscernibility relation. Using the first strategy, we can directly acquire knowledge by the classical rough set theory. However, this strategy fills up unknown information by estimation, which may change the original information of incomplete information system. Therefore, we only introduce the second strategy in this thesis.

The unknown value covers two cases including “do not care” (expressed by “*”) and “lost” (expressed by “?”). The “do not care” unknown value is the “everything is possible” value in the set of attribute values. It means the unknown value is just missing but does exist. On the other hand, if the unknown value is "lost", the objects may be described incompletely not only because of our imperfect knowledge, but also because it may be definitely impossible to describe them with all of the attributes. Thus, lost unknown value is a non-existing one and it is not comparable with any other values.

Since our research just involves in "do not care" unknown values and they just generate in condition attribute values, we only discuss the model in this case. Firstly, we need to expand the concept of indiscernibility relation. And then, we can set up related rough set model on it.

3.2.4.1 Tolerance relation and the corresponding rough set

Definition 3-20 [100] Let I be an incomplete information system in which $A \subseteq AT$. The *tolerance relation* in terms of A is defined as follows.

$$TOL(A) = \{(x, y) \in U \times U: f(x, a) = f(y, a) \vee f(x, a) = * \vee f(y, a) = *\} \quad (3\text{-}21)$$

"$*$" is referred to as equivalent to any other values in the domain of the corresponding attribute.

It is easy to prove that tolerance relation is reflexive and symmetric, but it is not necessarily transitive.

Given an incomplete information system I, $\forall\, x \in U$, the *tolerance class* of x in terms of is defined by

$$TOL_A(x) = \{y \in U: (x, y) \in TOL(A)\} \quad (3\text{-}22)$$

Obviously, it is different from equivalent class that an element in U may be included in different tolerance class simultaneously.

Definition 3-21 [100] Let I be an incomplete information system in which $A \subseteq AT$. $\forall\, X \subseteq U$, the *Lower Approximation* $\underline{TOL_A}(X)$ and *Upper Approximation* $\overline{TOL_A}(X)$ of X in terms of tolerance relation $TOL(A)$ are defined respectively as follows.

$$\underline{TOL_A}(X) = \{x \in U: TOL_A(x) \subseteq X\} \quad (3\text{-}23)$$

$$\overline{TOL_A}(X) = \{x \in U: TOL_A(x) \cap X \neq \emptyset\} \quad (3\text{-}24)$$

3.2.4.2 Reduct of incomplete information system in terms of Tolerance relation

Definition 3-22 [100] Let I be an incomplete information system, $A \subseteq AT$.

A is referred to as a *tolerance relation consistent attributes set* in I if $TOL(A) = TOL(AT)$.

$\forall\, B \subseteq A$, B is referred to as a *tolerance relation reduct* in I if A is a tolerance relation consistent attributes set in I and B is not the tolerance relation consistent attributes set in I.

Definition 3-23 [100] Let I be an incomplete information system. The tolerance relation discernibility attributes set in I is define by

$$DIS^T(x,y) = \begin{cases} \{a \in AT: (x,y) \notin TOL(\{a\})\}, & (x,y) \notin TOL(AT) \\ \emptyset, & otherwise \end{cases} \quad (3\text{-}25)$$

$\boldsymbol{M}^T = \left(DIS^T(x,y)\right)$ is called as the tolerance relation discernibility matrix.

All reducts of an incomplete information system can be given by the following tolerance relation discernibility function in I.

$$\Delta^T = \bigwedge_{DIS^T(x,y)} \left(\bigvee DIS^T(x,y) \right) \quad (3\text{-}26)$$

3.2.4.3 Incomplete decision system and generalized decision reduct

Definition 3-24 [100] Let I be an incomplete decision system with a decision attribute. Define a function

$$\partial_{AT}^T: U \to P(V_d)$$

$$\partial_{AT}^T(x) = \{f(x,d): y \in TOL_A(x)\}$$

∂_{AT}^T is called as the tolerance relation generalized decision in I, and $P(V_d)$ is the power set of the domain of the decision attribution d.

Obviously, I is consistent if $TOL(A) \subseteq IND(\{d\})$ for each $x \in U$; otherwise, I is inconsistent.

Definition 3-25 [100] Let I be an incomplete decision system, $A \subseteq AT$.

A is a *tolerance relation generalized decision consistent attributes set* in I if $\partial_A^T = \partial_{AT}^T$.

$\forall B \subseteq A$, B is a *tolerance relation generalized decision reduct* in I if A is a tolerance relation generalized decision consistent attributes set in I and B is not the tolerance relation generalized decision consistent attributes set in I.

A is a *tolerance relation generalized decision consistent attributes set* for x in I if $\partial_A^T(x) = \partial_{AT}^T(x)$.

$\forall B \subseteq A$, B is referred to as a *tolerance relation generalized decision reduct* in I for x if A is a tolerance relation generalized decision consistent attributes set for x in I and B is not the tolerance relation generalized decision consistent attributes set for x in I.

The tolerance relation generalized decision discernibility matrix in I is

$$\boldsymbol{M}_G^T = \left(DIS^T(x,y)\right), \quad x \in U, f(y,d) \notin \partial_{AT}^T(x) \quad (3\text{-}27)$$

$\forall x \in U$, The tolerance relation generalized decision discernibility matrix for x in I is

$$\boldsymbol{M}_G^T(x) = \left(DIS^T(x,y)\right), \quad f(y,d) \notin \partial_{AT}^T(x) \quad (3\text{-}28)$$

All reducts of an incomplete decision system can be given by the following tolerance generalized discernibility functions in I.

$$\Delta_G^T = \bigwedge_{DIS^T(x,y)\in \boldsymbol{M}_G^T} \left(\bigvee DIS^T(x,y) \right) \tag{3-29}$$

$$\Delta_G^T(x) = \bigwedge_{DIS^T(x,y)\in \boldsymbol{M}_G^T(x)} \left(\bigvee DIS^T(x,y) \right) \tag{3-30}$$

3.3 Genetic Algorithm (GA)

As early as in 1954, people started computer simulation of evolution [104]. In 1957, the Australian quantitative geneticist Alex Fraser published a series of papers on simulation of artificial selection of organisms with multiple loci controlling a measurable trait[105]. From these beginnings, computer simulation of evolution by biologists became more common.

A genetic algorithm (GA) is a metaheuristic inspired by the process of natural selection that belongs to the larger class of evolutionary algorithms (EA) [106]. Genetic algorithms are commonly used to generate high-quality solutions to optimization and search problems by relying on bio-inspired operators such as selection, crossover and mutation.

In a genetic algorithm, a population of candidate solutions (called individuals, creatures, or phenotypes) to an optimization problem is evolved toward better solutions. Each candidate solution has a set of properties (its chromosomes or genotype) which can be mutated and altered; traditionally, solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible.

The evolution usually starts from a population of randomly generated individuals, and is an iterative process, with the population in each iteration called a generation. In each generation, the fitness of every individual in the population is evaluated; the fitness is usually the value of the objective function in the optimization problem being solved. The more fit individuals are stochastically selected from the current population, and each individual's genome is modified (recombined and possibly randomly mutated) to form a new generation. The new generation of candidate solutions is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population.

A typical genetic algorithm covers a genetic representation of the solution domain and a fitness function to evaluate the solution domain. A standard representation of each candidate solution is as an array of bits. Arrays of other types and structures can be used in essentially the same way. The main property that makes these genetic representations convenient is that their parts are easily aligned due to their fixed size, which facilitates simple crossover operations. Variable length representations may also be used, but crossover implementation is more complex in this case. Tree-like representations are explored in genetic programming and graph-form representations are explored in evolutionary programming: a mix of both linear chromosomes and trees is explored in gene expression programming.

Once the genetic representation and the fitness function are defined, a GA proceeds to initialize a population of solutions and then to improve it through repetitive application of the mutation, crossover, inversion and selection operators.

The population size depends on the nature of the problem, but typically contains several hundreds or thousands of possible solutions. Often, the initial population is generated randomly, allowing the entire range of possible solutions (the search space). Occasionally, the solutions may be “seeded” in areas where optimal solutions are likely to be found.

The process of genetic operators is as follows.

3.3.1 Selection

During each successive generation, a proportion of the existing population is selected to breed a new generation. Individual solutions are selected through a fitness-based process, where fitter solutions (as measured by a fitness function) are typically more likely to be selected. Certain selection methods rate the fitness of each solution and preferentially select the best solutions. Other methods rate only a random sample of the population, as the former process may be very time-consuming.

The fitness function is defined over the genetic representation and measures the quality of the represented solution. The fitness function is always problem dependent. For instance, in the knapsack problem one wants to maximize the total value of objects that can be put in a knapsack of some fixed capacity. A representation of a solution might be an array of bits, where each bit represents a different object, and the value of the bit (0 or 1) represents whether or not the object is in the knapsack. Not every such representation is valid, as the size of objects may exceed the capacity of the knapsack. The fitness of the solution is the sum of values of all objects in the knapsack if the representation is valid or 0 otherwise.

In some problems, it is hard or even impossible to define the fitness expression; in these cases, a simulation may be used to determine the fitness function value of a phenotype (e.g. computation fluid dynamics is used to determine the air resistance of a vehicle whose shape is encoded as the phenotype), or even interactive genetic algorithms are used.

3.3.2 Crossover and mutation

For each new solution to be produced, a pair of “parent” solutions is selected for breeding from the pool selected previously. By producing a “child” solution using the above methods of crossover (also called recombination) and mutation, a new solution is created which typically shares many of the characteristics of its “parents”. New parents are selected for each new child, and the process continues until a new population of solutions of appropriate size is generated. Although reproduction methods that are based on the use of two parents are more “biology inspired”, some research suggests that more than two “parents” generate higher quality chromosomes.

These processes ultimately result in the next generation population of chromosomes that is different from the initial generation. Generally the average fitness will have increased by this procedure for the population, since only the best organisms from the first generation are selected for breeding, along with a small proportion of less fit solutions. These less fit solutions ensure genetic diversity within the genetic pool of the parents and therefore ensure the genetic diversity of the subsequent generation of children.

It is worth tuning parameters such as the mutation probability, crossover probability and population size to find reasonable settings for the problem class being worked on. A very small mutation rate may lead to genetic drift (which is non-ergodic in nature). A recombination rate that is too high may lead to premature convergence of the genetic algorithm. A mutation rate that is too high may lead to loss of good solutions, unless elitist selection employed.

3.3.3 Termination Condition

This generational process is repeated until a termination condition has been reached. Common terminating conditions are as follows. (1) A solution is found that satisfies minimum criteria; (2) Fixed number of generations reached; (3) Allocated budget (computation time/money) reached; (4) The highest ranking solution’s fitness is reaching or has reached a plateau such that successive iterations no longer produce better results; (5) Manual inspection; (6) Combinations of the above.

3.4 Semantic differential method

Semantic Differential (SD) is a type of a rating scale designed to measure the connotative meaning of objects, events, and concepts. The connotations are used to derive the attitude towards the given object, event or concept.

Osgood's Semantic Differential [91] was an application of his more general attempt to measure the semantics or meaning of words, particularly adjectives, and their referent concepts. The respondent is asked to choose where his or her position lies, on a scale between two polar adjectives (for example: “Adequate-Inadequate”, “Good-Evil” or “Valuable-Worthless”). Semantic differentials can be used to measure opinions, attitudes and values on a psychometrically controlled scale.

It usually considers five, seven or nine measuring scale, and is respectively called as five-point scale, seven-point scale and nine-point scale. The subjects are asked to score samples. They are usually described by introducing some adjectives such as “extreme”, “very”, “fairly”, “a little”, and so on. For example, we describe the softness of fabrics by using seven-point scale between two polar adjectives “soft-hard”. The scales can be expressed by “extreme soft”, “soft”, “a little soft”, “neutral”, “a little hard”, “hard” and “extreme hard”.

3.5 Applications in the Proposed System

In this chapter, we introduce the major computational methods used in our research.

Since the linguistic data obtained from our sensory experiments are fuzzy and uncertain, and cannot be expressed accurately, the theories of fuzzy sets and rough sets play a major role in our approaches of modeling and analysis.

Fuzzy sets theory is the most important technique in our research. Concretely, it is used to formalize the relationship between different data sets such as the set of evaluation data on body shapes and the set of style elements. Different fuzzy membership functions are defined to represent the sensory data. The operations of fuzzy sets and fuzzy matrices are used to describe the concerned relations, such as that of body shapes and design styles. For classifying the results obtained from different sensory experiments into predefined standard models such as seven evaluation levels on fabric softness and fashion themes, we have introduced several methods of fuzzy model recognition (maximal membership principle, threshold principle, …). Fuzzy model recognition is an efficient method for establishing the relational models between linguistic data acquired from sensory experiments and determining the belonging (not unique) or combination of a specific object with respect to a set of standard models. For example, a fashion theme is described by a seven-points scale, regarded as a set of seven standard models. The purpose of our study is to identify to which standard model or level of the fashion theme a specific design factor (style, fabric or color) is the most relevant. Combined with the procedure of fuzzy comprehensive evaluation presented in Section 3.1.6, the fuzzy relational models proposed in my thesis constitute the main inference engine in the design-oriented recommendation system by computing close degrees between different fuzzy sets. These fuzzy relational models also constitute the basis for establishing the design knowledge base, updated progressively with new design cases and integrated into the recommendation system. Moreover, in the procedure of fuzzy comprehensive evaluation, we have used the Analytic Hierarchy Process (AHP) for identifying the weights of the evaluation criteria. AHP is a relevant method in our context because it can effectively process qualitative comparison data provided by different human evaluators for obtaining significant weights.

In my thesis, rough sets theory is also used to set up the classification models for fabrics and body shapes and extract IF…THEN rules on relations between fabric technical parameters and corresponding sensory properties. Compared with fuzzy techniques, rough sets theory is more adapted to modeling with incomplete data and does not require involvement of human knowledge. For identifying the optimal solution in multi-criteria classification model of body shapes, we obtain the classification index at each body position by using linear regression analysis. In modeling the relationship between technical parameters of fabrics and sensory properties, we have applied fuzzy sets to discretize technical parameters measured and used rough sets method to exact related rules from incomplete measured data. These results will be stored in the knowledge base of the recommendation system for further use.

A Genetic Algorithm is used in the recommendation system for progressively updating the knowledge base (rules extracted by rough sets, fuzzy relational models, and close degrees between fuzzy sets) from new design cases. It permits to set up a self-adjusting mechanism in the proposed design-oriented recommendation system. In this situation, new recommended design solutions can be generated from this mechanism according to the sensory evaluations of designers on the current products.

Semantic Differential method is used in sensory experiments for expressing the results of sensory evaluation.

CHAPTER 4 MODELING OF HUMAN BODY SHAPES AND DESIGN KNOWLEDGE

In this chapter, we mainly discuss the mathematical models related to garment design. First, we set up the body shapes classification model using body measurements according to their sensitivity to designer's perception. Next, we set up four relational models between various design factors (fashion themes, design styles, fabric properties and colors) according to the results of sensory experiments. In each part, we provide an illustrative example and all the models have been implemented using MATLAB software.

4.1 Classification Model for Lower Body Shapes (Model 1)

In this Section, we set up a supervised learning model permitting to classify body measurements according to designer's perceptions on lower human body shapes. First, we acquire the data on various dimensions of 118 selected human bodies (see Section 2.1) accurately by using the 3D body scanning technique and transform these measured body dimensions into the characteristic body indices of six lower body positions (input data). Next, these 118 virtual human models are evaluated by a number of designers according to their perceptions and experiences (output data) (see Experiment 3). The main idea of this classification model is to extract rules characterizing the relation between the above input and output data. As there exists a strong correlation between different body indices of each body position, we define for each body position a classification index, which is aggregated from the corresponding body indices. Considering the vagueness and imprecision of human's perceptions, we classify data of each classification index into five levels (scores) by using fuzzy techniques. The different combinations of levels for all the six classification indices (six body positions) constitute all the possible lower body shapes.

The experimental results have shown that the classification model is completely acceptable by designers in terms of their perception.

4.1.1 The classification of different lower body positions

In my research, we will model the classification for each lower body position respectively based on the lower body indices presented in Chapter 2. For each body position, for simplicity, we propose to define a unidimensional aggregated classification index and classify body shapes with this index. However, if the indices of a body position are not strongly correlated, we have to consider the body shape classification with all the corresponding body indices.

4.1.1.1 Identification of the classification index of each body position

As we know, the linear relation is the simplest relation between variables. Therefore, we first test the linear correlation between the corresponding body indices and designer's perceptions on body shapes by linear regression analysis [107] for each body position. In order to apply the regression Equation, the linguistic evaluation scores on body shapes (from "*very small*" to "*very large*") are transformed into numbers 1 ~ 5.

For the hip position, we set up a linear regression Equation (4-1) by taking the three normalized hip shape indices hs_1, hs_2 and hs_3 (Section 2.1.2) as independent variables and the human perception on hip shape y as dependent variable.

$$y = k_0 + k_1 hs_1 + k_2 hs_2 + k_3 hs_3 + \varepsilon \quad (4\text{-}1)$$

where ε is the residual error.

Assuming that the confidence level is $\gamma = 95\%$. After introducing all the sample data to the Equation, we have

$$y = 3.0339 + 0.4851hs_1 + 0.0239hs_2 + 0.3238hs_3 + \varepsilon_1 \quad (4\text{-}2)$$

where the F-test value is $F = 124.0072$, the F-test threshold of this regression equation is $f = 9.5619\times10^{-36}$ $(F > f)$, the mean square error of the residual error $RMSE = 0.8764$, the determinant coefficient $R^2 = 0$ and the significance probability $p = 0.7654 < \gamma$. Evidently, we can find that the linear relation of all the input variables hs_1, hs_2, hs_3 and the dependent variable y cannot be validated due to the fact that the significance probability is smaller than the confidence level.

In this situation, we adopt the stepwise regression method [108] by progressively integrating one then two variables to the regression Equation in order to find the best linear form, leading to the minimal value of $RMSE$. By learning from the specific data of hip position, we obtain the best linear regression form and the residual plot as follows.

$$y = 3.0339 + 0.5119hs_1 + 0.3189hs_3 + \varepsilon_2 \quad (4\text{-}3)$$

where $F = 187.63$, $f = 6.1743\times10^{-37}$, $RMSE = 0.4281$, and $R^2 = 0.7654$.

Figure 4-1 shows the residual errors of all the data.

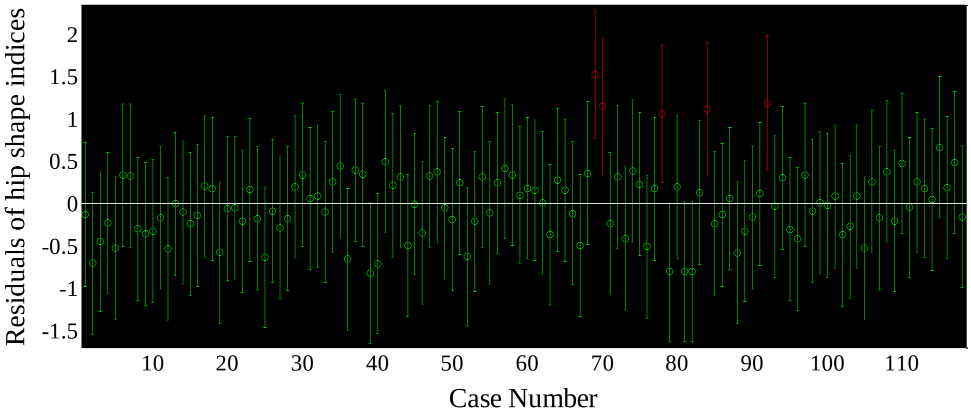


Figure 4-1 The residual case order plot of hip shape indices

Obviously, the residual errors of these data are closer to 0 except five outliers. Moreover, the corresponding significance probability p $(= 1 - f)$ is very close to 1 and much bigger than the confidence level γ. Therefore, the linear relation between hs_1 and hs_3 and y can be validated. Also, the body index hs_2 is removed. Evidently, this index is the origin of the nonlinear relation in Equation (4-2). By computing with the learning data, we can find that the correlation between hs_1 and hs_2 is very strong ($\rho(hs_1, hs_2) = 0.9809$). Therefore, removing hs_2 from the regression Equation is completely acceptable.

According to the previous discussion, we take the linear combination of hs_1 and hs_3 as the classification index of hip position, denoted as HS. i.e.

$$HS = 3.0339 + 0.5119hs_1 + 0.3189hs_3 \quad (4\text{-}4)$$

Similar to the analysis on hip position, we can obtain the classification index of abdomen position, denoted as AS. i.e.

$$AS = 2.8051 + 0.2612as_1 + 0.6449as_3 \quad (4\text{-}5)$$

The residual plot is as Figure 4-2 ($RMSE = 0.4633$, $R^2 = 0.7654$ and $p = 3.66821 \times 10^{-38} > \gamma$).

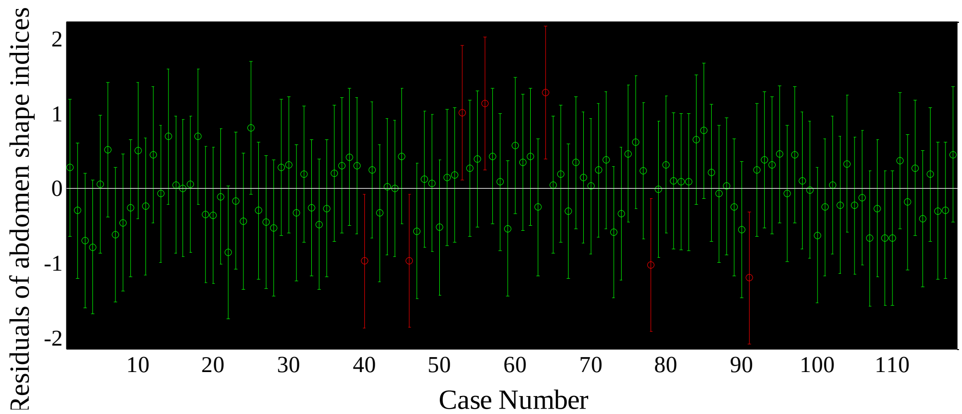


Figure 4-2 The residual case order plot of abdomen shape indices

The classification index of leg length, denoted as LL, satisfies

$$LL = 2.7627 + 0.3753ll_1 + 0.4157ll_2 \tag{4-6}$$

The residual plot is as Figure 4-3 ($RM \quad = 0.3771$, $R^2 = 0.7572$ and $p = 4.47157\times10^{-36} > \gamma$).

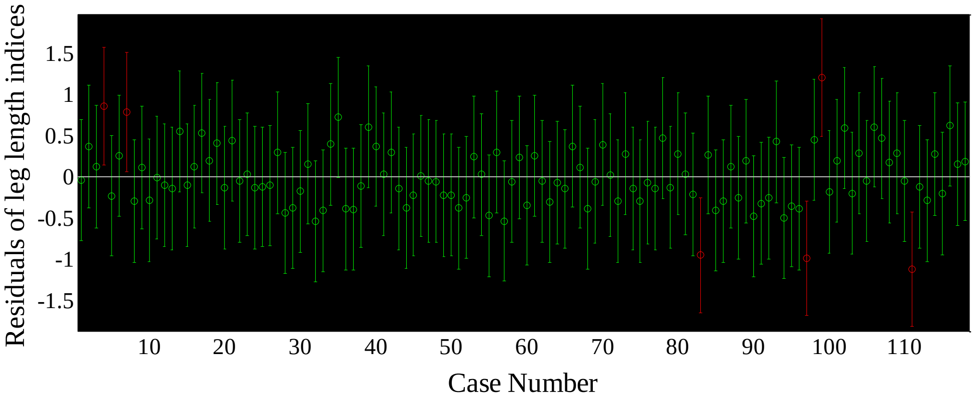


Figure 4-3 The residual case order plot of leg length indices

The classification index of thigh position, denoted as TS, satisfies

$$TS = 2.6949 + 0.2106ts_2 + 0.7797ts_3 \tag{4-7}$$

The residual plot is as Figure 4-4 ($RMSE = 0.4740$, $R^2 = 0.7865$ and $p = 2.75412\times10^{-39} > \gamma$).

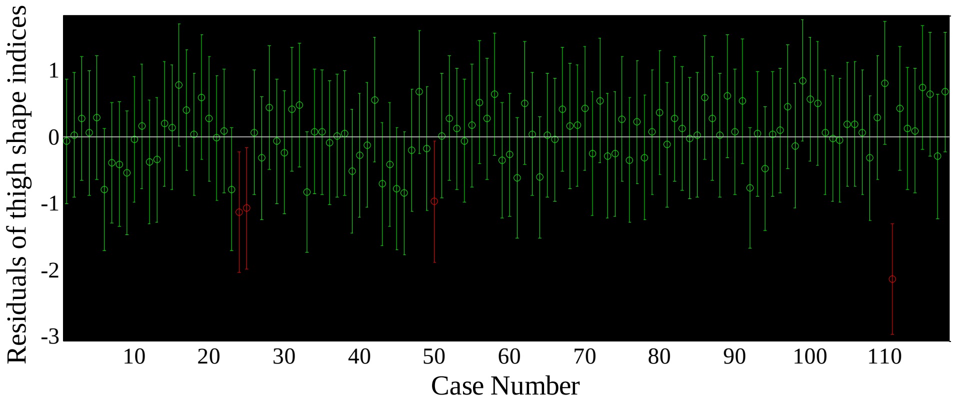


Figure 4-4 The residual case order plot of thigh shape indices

The classification index of calf position, denoted as CS, satisfies

$$CS = 3.0593 + 0.3516cs_2 + 0.3675cs_3 \tag{4-8}$$

The residual plot is as Figure 4-5 ($RMSE = 0.4764$, $R^2 = 0.6404$ and $p = 2.87773\times10^{-26} > \gamma$).

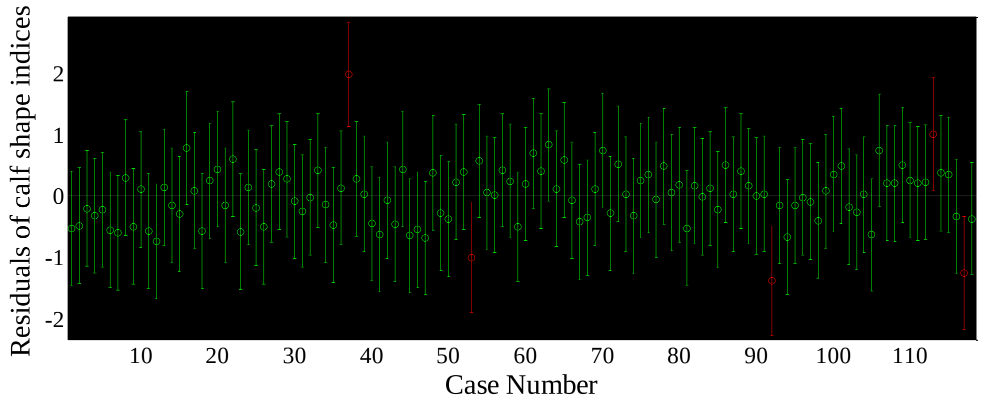


Figure 4-5 The residual case order plot of calf shape indices

The classification index of waist position, denoted as WS. i.e.

$$WS = 2.8644 + 0.7806\, ws \tag{4-9}$$

The residual plot is as Figure 4-6.

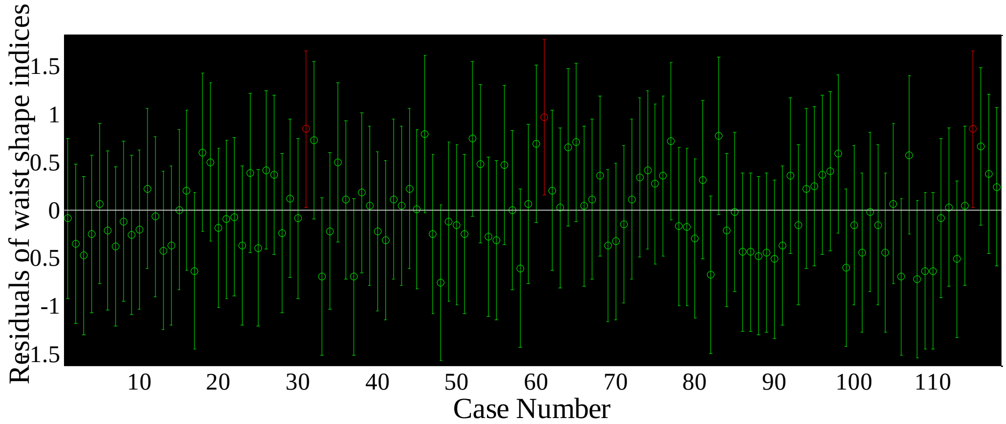


Figure 4-6 The residual case order plot of waist shape indices

All the symbols of body indices used in these Equations have been defined in Section 2.1.2. From these results, we can conclude that the body shape at each positon can be characterized by a classification index, generated from linear combination of its corresponding body indices. Therefore, each lower body shape can be expressed by one 6-dimensional body shape vector $bs = (WS, HS, AS, LL, TS, CS)$.

Since the body shapes described by linguistic terms are more significant in garment design, the previously defined classification indices are transformed into fuzzy sets.

4.1.1.2 Fuzzification of the classification index values

Let the j-th classification index value of the i-th human body b_i in the human bodies set B be x_{ij} $(i = 1, \dots, n; j = 1,2, \dots, 6)$.

In our study, the classification indices take values from the set of evaluation scores {*VS* (*Very Small*), *S* (*Small*), *M* (*Middle*), *L* (*Large*), *VL* (*Very Large*)}. For obtaining five fuzzy sets expressed by five evaluation levels (scores), we denote the following five numerical values.

$$X_1^{(j)} = \min_{1 \le i \le n}\{x_{ij}\} \tag{4-10}$$

$$X_3^{(j)} = \operatorname*{median}_{1 \le i \le n}\{x_{ij}\} \tag{4-11}$$

$$X_5^{(j)} = \max_{1 \le i \le n}\{x_{ij}\} \tag{4-12}$$

$$X_2^{(j)} = \frac{X_1^{(j)} + X_3^{(j)}}{2} \tag{4-13}$$

$$X_4^{(j)} = \frac{X_3^{(j)} + X_5^{(j)}}{2} \tag{4-14}$$

Using these five values, the fuzzy sets can be expressed by $\tilde{C}_1 = \text{Trapezoid}(0, 0, X_1^{(j)}, X_2^{(j)})$, $\tilde{C}_2 = \text{Triangle}(X_1^{(j)}, X_2^{(j)}, X_3^{(j)})$, $\tilde{C}_3 = \text{Triangle}(X_2^{(j)}, X_3^{(j)}, X_4^{(j)})$, $\tilde{C}_4 = \text{Triangle}(X_3^{(j)}, X_4^{(j)}, X_5^{(j)})$, and $\tilde{C}_5 = \text{Trapezoid}(X_4^{(j)}, X_5^{(j)}, \infty, \infty)$.

We select the median value rather than mean value because it cannot be influenced by the extreme values and doesn't always alter with the change of samples.

Each classification index value x_{ij} $(i = 1, \dots, n; j = 1,2, \dots, 6)$ can be expressed by a vector on the basis of the five fuzzy sets $\tilde{C}_1, \tilde{C}_2, \tilde{C}_3, \tilde{C}_4, \tilde{C}_5$ each having a triangle or trapezoidal membership function (Figure 4-7).

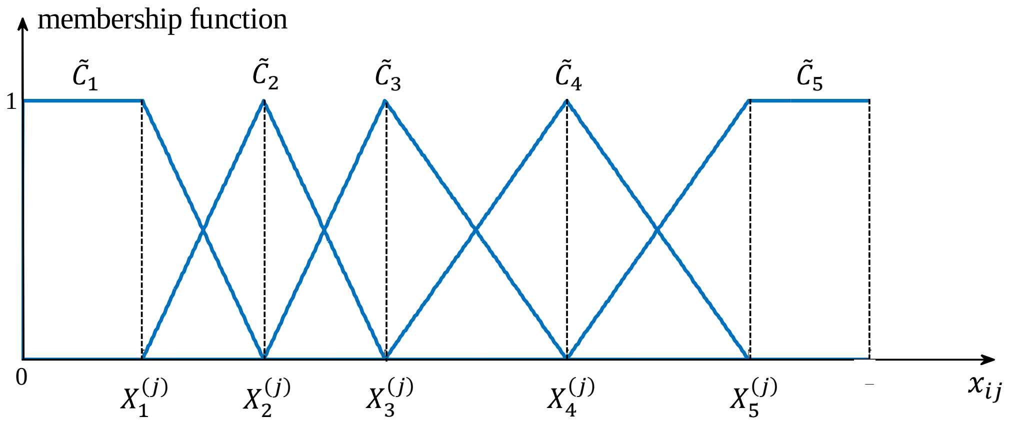


Figure 4-7 Fuzzy membership functions of the body shape data

The vector of membership degrees of x_{ij}, also called fuzzy distribution, is denoted as $\left(\mu_{ij}^{(1)},\ \mu_{ij}^{(2)},\ \mu_{ij}^{(3)},\ \mu_{ij}^{(4)},\ \mu_{ij}^{(5)}\right)$, where $\mu_{ij}^{(k)}$ is the membership degree of the index value

$x_{ij}(i = 1, \ldots, n; j = 1,2, \ldots, 6)$ to the fuzzy set $\tilde{C}_k$ $(k = 1,2, \ldots, 5)$.

According to the Maximal Membership Principle Ⅰ (Section 3.1.5.1), $\bar{x}_{ij}$ is affected to $\tilde{C}_{k^*}$ if $\mu_{ij}^{(k^*)} = \vee_{k=1}^{m}\{\mu_{ij}^{(k)}\}$. The five fuzzy sets $\tilde{C}_1, \tilde{C}_2, \tilde{C}_3, \tilde{C}_4, \tilde{C}_5$ constitute the standard models base of the body shapes.

4.1.2 The classification of the lower body shapes

According to the discussion in Section 4.1.1, the shape of each body position can be classified by using the five fuzzy sets $\tilde{C}_1, \tilde{C}_2, \tilde{C}_3, \tilde{C}_4, \tilde{C}_5$.

From the human body data obtained in Experiments 1 (body dimensions) and 3 (body shape evaluation), we obtain the five key numerical values of the membership functions for each classification index as follows (Table 4-1).

Table 4-1 The five key numerical values of each classification index

	WS	*HS*	*AS*	*LL*	*TS*	*CS*
X_1	0.3636	0.9007	1.1273	0.8090	0.3304	1.2404
X_2	0.3941	1.9972	1.9243	1.7930	1.5815	2.1204
X_3	0.4246	3.0937	2.7213	2.7770	2.8325	3.0004
X_4	0.4750	4.0686	3.7891	3.5034	3.9305	3.8111
X_5	0.5253	5.0436	4.8568	4.2298	5.0284	4.6219

According to the proposed fuzzification method, each classification index can be transformed into a fuzzy value, shown in Appendix 1 (2).

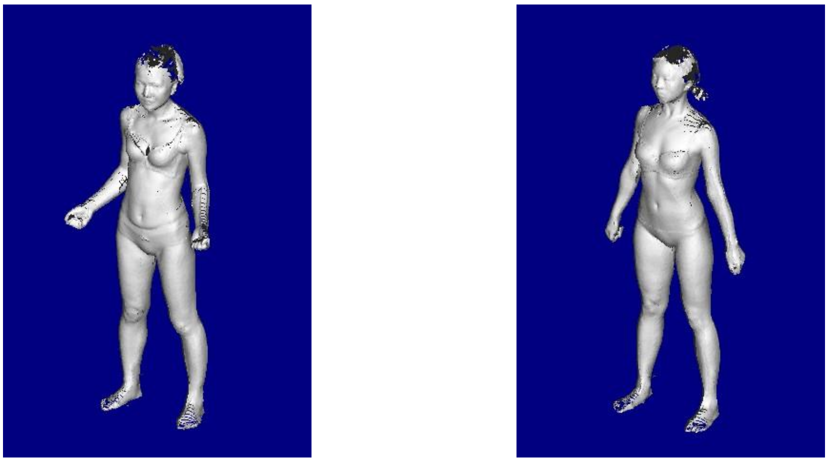
Then, we set up a discrete information system (data table), in which the overall six classification indices are taken as conditional attributes for modeling the lower body shapes. Using the equivalent classification method of information system, all the body shapes are divided into 103 classes according to the shapes of 6 lower body positions. It can be seen that the generated body shapes in the whole population are rather distinct one from another. The computational details can be shown in the following example.

4.1.3 An illustrative example

Here we discuss two real examples. By using the 3D body scanning, we obtain the 8 key dimensions (see Section 2.1.1) for two real human bodies body_1 and body_2 (Figure 4-8), and these two measure vectors are as follows.

$$measure_{\text{body}_1} = (\overset{S}{165.2}, \ \overset{WH}{101.4}, \ \overset{CH}{72.6}, \ \overset{W}{67.2}, \ \overset{H}{88.8}, \ \overset{A}{75.9}, \ \overset{TG}{49.0}, \ \overset{CG}{33.6})$$

$$measure_{\text{body\_2}} = (\overset{S}{166.6},\ \overset{WH}{105.0},\ \overset{CH}{76.3},\ \overset{W}{66.0},\ \overset{H}{91.6},\ \overset{A}{77.6},\ \overset{TG}{55.0},\ \overset{CG}{32.7})$$



(a) body_1 (b) body_2

Figure 4-8 3D scanning pictures of two real bodies

We can compute the lower body index values of these two human bodies using the Equation (2-1) ~ (2-6) in Chapter 2.

According to these body index values and the Equation (4-4) ~ (4-9), we obtain the body shape vectors of these two human bodies (body_1 and body_2).

$$bs_{\text{body\_1}} = (\overset{WS}{3.1819},\ \overset{HS}{3.2330},\ \overset{AS}{2.6725},\ \overset{LL}{2.5771},\ \overset{TS}{2.8796},\ \overset{CS}{2.7790})$$

$$bs_{\text{body\_2}} = (\overset{WS}{3.1737},\ \overset{HS}{3.6697},\ \overset{AS}{2.9129},\ \overset{LL}{3.0416},\ \overset{TS}{4.2743},\ \overset{CS}{2.3732})$$

According to the proposed classification algorithm, the classification indices can be fuzzified as

$$\text{fuzzify}(bs_{\text{body\_1}}) = (\overset{WS}{\tilde{C}_2},\ \overset{HS}{\tilde{C}_3},\ \overset{AS}{\tilde{C}_3},\ \overset{LL}{\tilde{C}_3},\ \overset{TS}{\tilde{C}_3},\ \overset{CS}{\tilde{C}_3})$$

$$\text{fuzzify}(bs_{\text{body\_2}}) = (\overset{WS}{\tilde{C}_2},\ \overset{HS}{\tilde{C}_4},\ \overset{AS}{\tilde{C}_3},\ \overset{LL}{\tilde{C}_3},\ \overset{TS}{\tilde{C}_4},\ \overset{CS}{\tilde{C}_2})$$

Therefore, two body shapes can be identified as follows.

The lower body shape of body_1 is $\left(WS^{(S)},\ HS^{(M)},\ AS^{(M)},\ LL^{(M)},\ TS^{(M)},\ CS^{(M)}\right)$, meaning that the waist shape is small, and the hip shape, the abdomen shape, the leg length, the thigh shape and the calf shape are all medium.

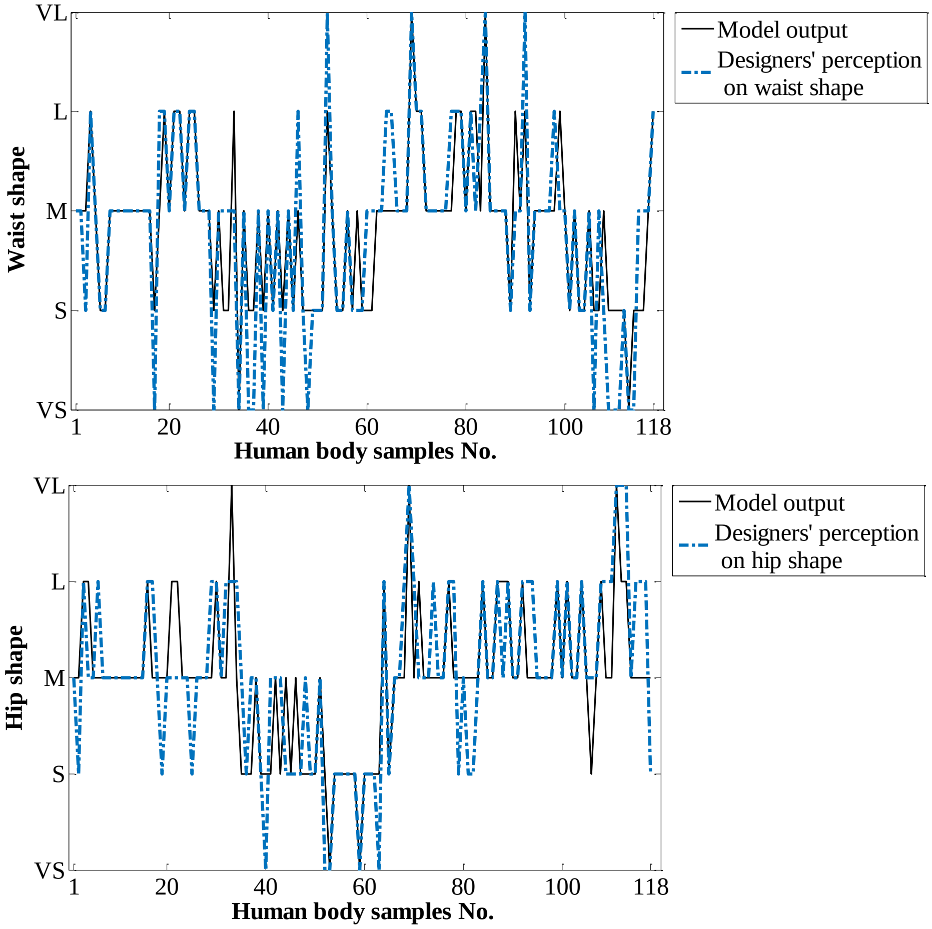
The lower body shape of body_2 is $\left(WS^{(S)},\ HS^{(L)},\ AS^{(M)},\ LL^{(M)},\ TS^{(L)},\ CS^{(S)}\right)$, meaning that both the waist shape and the calf shape are small, and both the hip shape and the thigh shape are large, and both the abdomen shape and the leg length are medium.

According to these results, we can easily compare two body shapes even if their statures are different. For example, both the hip and thigh of body_2 are larger than those of body_1.

4.1.4 Validation of the model

In our research, since the classification results of body shapes will be used in garment design, they have to conform to the perceptions of designers. Therefore, we validate the proposed classification model by evaluating whether the model output and the perception of designers are consistent or not.

This validation is performed on the whole population of 118 effective human models created in Chapter 2. The results delivered by both the classification model and the designer's evaluations on shapes of various body positions are shown in Figure 4-9.



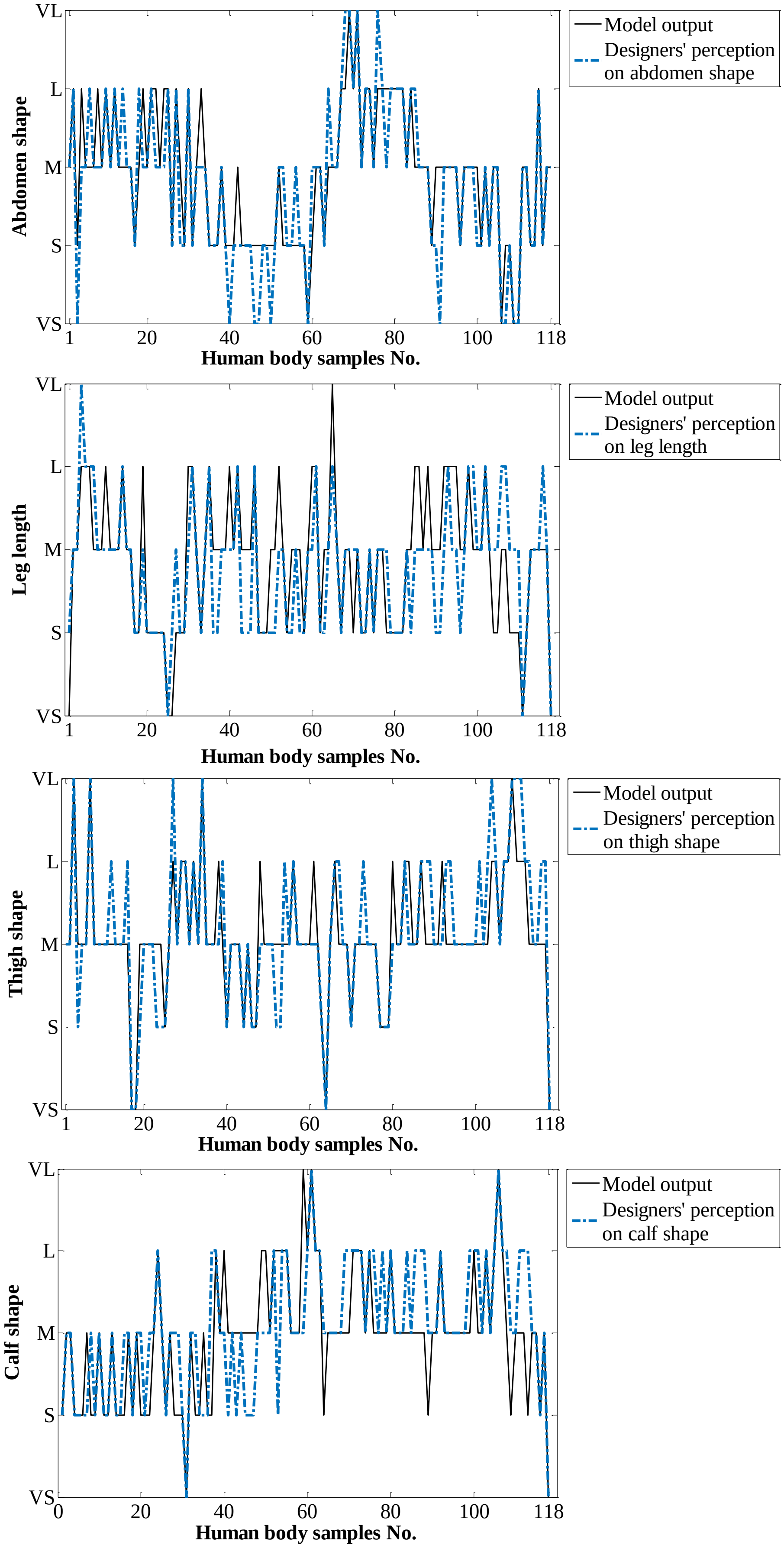


Figure 4-9 Comparison between results of the model and human perceptions on body shapes

The difference between two results is expressed by Model_Error, whose definition is as follows.

Let the set of all results delivered by the model be $X = \{x_1, x_2, \dots, x_n\}$ and the set of designer's perceptions be $Y = \{y_1, y_2, \dots, y_n\}$. The criterion of Model_Error is defined as

$$\text{Model\_Error}(X, Y) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2} \quad (4\text{-}15)$$

In this Equation, all the results $x_i, y_i \in \{1,2 \dots ,5\}$. The values of Model_Error for all the body positions are listed in Table 4-2.

Table 4-2 The values of Model_Error for each body position

	Waist shape	Hip shape	Abdomen shape	Leg length	Thigh shape	Calf shape
Model Error	0.5446	0.5966	0.5126	0.6037	0.5126	0.5126

All these errors are no more than 0.6, meaning that the error of human data is lower than 0.6 level of 5 (<12%) in average. Therefore, we can believe that the proposed model is acceptable.

4.2 Modeling the relationship between Body Shapes and Basic Design Styles (Model 2)

In this Section, we set up the relational model between various body shapes and basic design styles by using fuzzy techniques. The flow diagram of Model 2 is shown in Figure 4-10 and the details of modeling are given in the following Section.

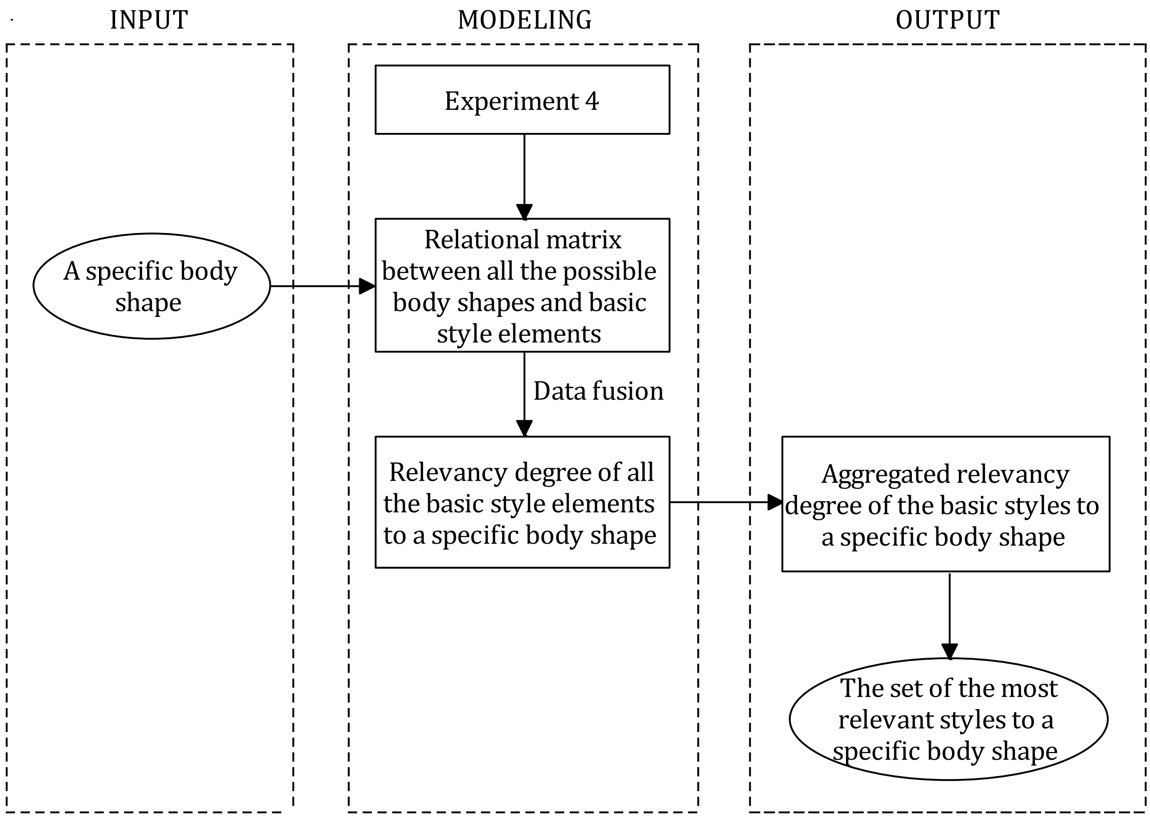


Figure 4-10 Functional Structure of Model 2

4.2.1 Fuzzification and formulization of evaluation results

From the Experiment 4 in Chapter 2, the evaluation scores come from the linguistic set of $\{unfit, neutral, fit\}$, which can be expressed respectively by three fuzzy sets $\tilde{A}_1, \tilde{A}_2, \tilde{A}_3$ with the property of "bilateral symmetry and middle value is higher than bilateral ones". These three fuzzy sets are considered as standard evaluation scores (levels) in our following computation. Assume "unfit", "neutral" and "fit" be expressed respectively by "-1", "0" and "1". Thus, these three fuzzy sets can be expressed by using three "middle type" membership functions $\mu_{\tilde{A}_i}(x)$ $(k = 1,2,3)$ defined on the interval $[-1, 1]$, and in the same coordination system, they should follow the condition below.

1) The coordinates of their peaks are $(-1, 1)$, $(0, 1)$ and $(1, 1)$ respectively;
2) The other two values are 0 if one value is 1;
3) The intersection of two adjacent membership functions corresponds to 0.5 in the ordinate direction (the maximal fuzziness).

For simplicity, we propose the three triangular membership functions as follows.

$$\mu_{\tilde{A}_k}(x) = \begin{cases} x - k + 1, & \text{if } \max\{-1, k-1\} \le x \le k \\ -x + k + 1, & \text{if } k \le x \le \min\{1, k+1\} \\ 0, & \text{otherwise} \end{cases} \quad (k = 1,2,3) \tag{4-16}$$

They are showed in Figure 4-11.

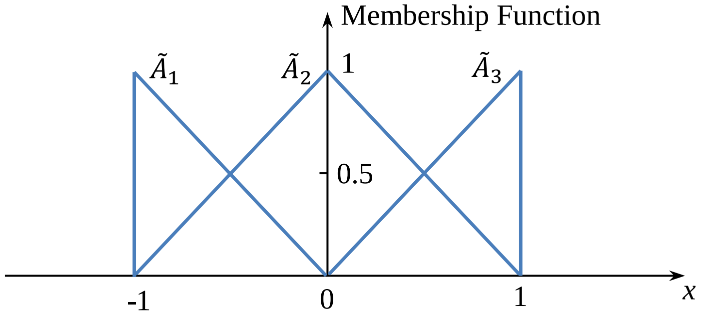


Figure 4-11 The three membership functions of evaluation scores

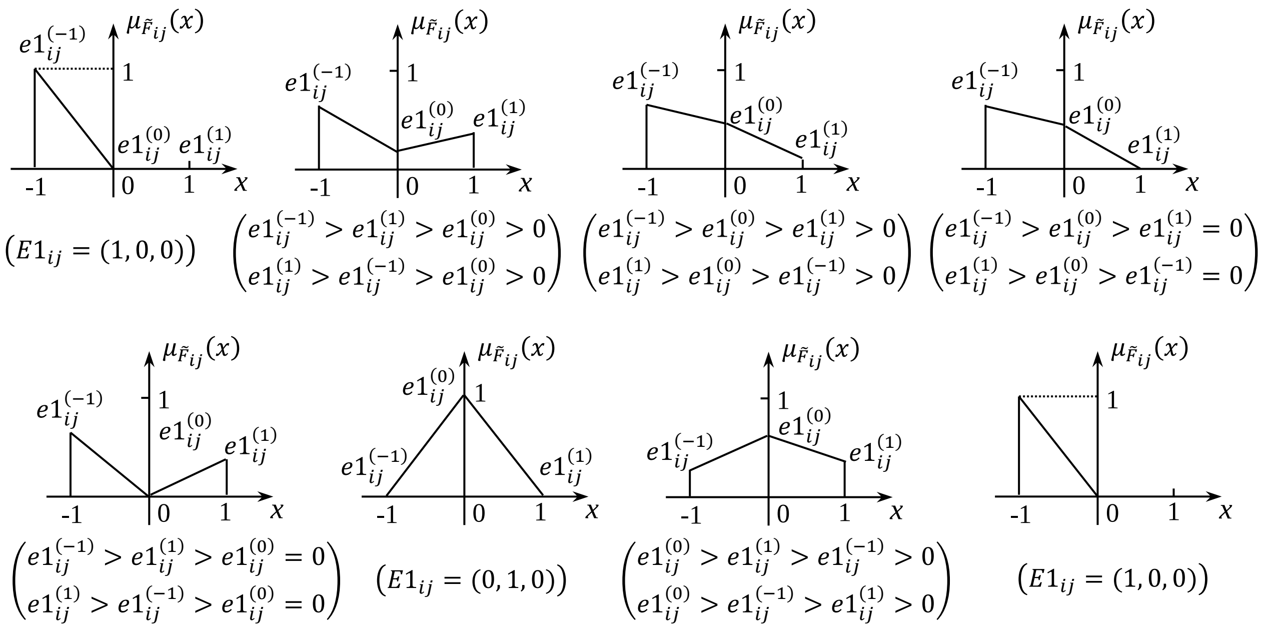
We assume that $r1_{ij}^{(k)}$ the number of people (among all the r panelists) give the evaluation score k $(k \in \{-1,0,1\})$ on the relevancy of the j-th $(j \in \{1, \ldots, K_1\})$ basic style element (The set of all the K_1 basic style elements is $\{\underbrace{PATTERN_1}_{D_1}, \underbrace{PATTERN_2}_{D_2}, \underbrace{PATTERN_3}_{D_3}, \underbrace{PATTERN_4}_{D_4},$ $\underbrace{WAIST_1}_{D_5}, \underbrace{WAIST_2}_{D_6}, \underbrace{WAIST_3}_{D_7}, \underbrace{LEG_1}_{D_8}, \underbrace{LEG_2}_{D_9}, \underbrace{LEG_3}_{D_{10}}, \underbrace{LEG_4}_{D_{11}}\}$, see Section 2.5.2) to the i-th $(i \in \{1, \ldots, \lambda\})$ possible type of body shape (The set of the λ types of possible body shapes is $BS = \{WS^{(VS)}, WS^{(S)}, WS^{(M)}, WS^{(L)}, WS^{(VL)}, HS^{(VS)}, HS^{(S)}, HS^{(M)}, HS^{(L)}, HS^{(VL)}, AS^{(VS)}, AS^{(S)},$ $AS^{(M)}, AS^{(L)}, AS^{(VL)}, LL^{(VS)}, LL^{(S)}, LL^{(M)}, LL^{(L)}, LL^{(VL)}, TS^{(VS)}, TS^{(S)}, TS^{(M)}, TS^{(L)}, TS^{(VL)}, CS^{(VS)}, CS^{(S)},$ $CS^{(M)}, CS^{(L)}, CS^{(VL)}\}$).

The concerned symbols have been defined in Section 2.4.2.

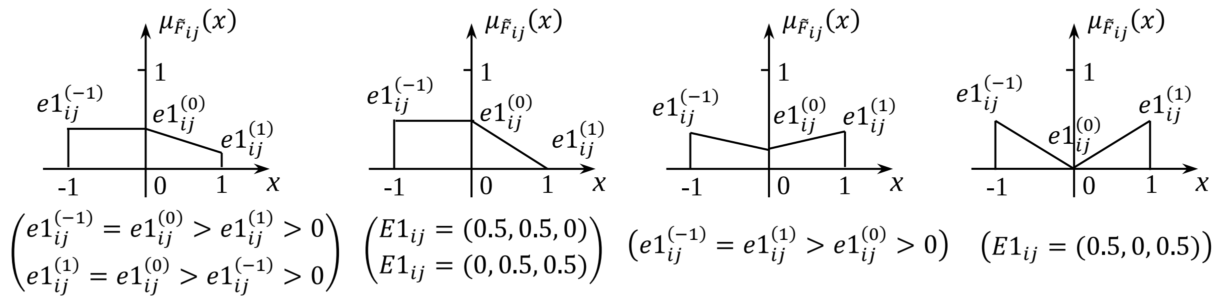
The evaluation results of all the panelists can be expressed by a fuzzy distribution:

$$\widetilde{E1}_{ij} = \left(\frac{r1_{ij}^{(-1)}}{r}, \frac{r1_{ij}^{(0)}}{r}, \frac{r1_{ij}^{(1)}}{r} \right) = \left(e1_{ij}^{(-1)}, e1_{ij}^{(0)}, e1_{ij}^{(1)} \right) \tag{4-17}$$

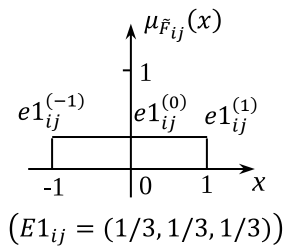
$\widetilde{E1}_{ij}$ is a fuzzy set, whose membership function $\mu_{\widetilde{E1}_{ij}}(x)$ is a triangle or polygonal (quadrilateral or pentagonal) function which takes the points $(-1, 0)$, $(-1, e1_{ij}^{(-1)})$, $(0, e1_{ij}^{(0)})$, $(1, e1_{ij}^{(1)})$ and $(1, 0)$ as vertexes (some points could be coincident). All types of possible membership functions of evaluation data are shown in Figure 4-12 (a) ~ (c).



(a) The membership function of evaluation distribution with one peak



(b) The membership function of evaluation distribution with two peaks



(c) The membership function of evaluation distribution with three peaks

Figure 4-12 The membership functions of all possible distributions of evaluation data

4.2.2 Relevancy between lower body shapes and basic style elements

We define the *Close Degree* of the distribution of evaluation data $\widetilde{E1}_{ij}$ on the j-th basic style element (D_j) related to the i-th type of possible body shapes, to the previously defined standard evaluation levels (scores) $\tilde{A}_k$' s (See Equation (4-16)) according to the Equation

(4-18).

$$r\left(\widetilde{E1}_{ij},\tilde{A}_k\right)=\frac{\int_{-1}^{1}\left[\mu_{\widetilde{E1}_{ij}}(x)\wedge\mu_{\tilde{A}_k}(x)\right]dx}{\int_{-1}^{1}\left[\mu_{\widetilde{E1}_{ij}}(x)\vee\mu_{\tilde{A}_k}(x)\right]dx} \tag{4-18}$$

Evidently, $r\left(\widetilde{E1}_{ij},\tilde{A}_k\right)$ is larger if $\widetilde{E1}_{ij}$ is closer to $\tilde{A}_k$ (i.e. the best evaluation score of the j-th basic style element related to the i-th body shape type) and it satisfies the following three properties for all close degrees [62].

(a) $0\le r\left(\widetilde{E1}_{ij},\tilde{A}_k\right)\le 1$, and $r\left(\widetilde{E1}_{ij},\tilde{A}_k\right)=1 \Leftrightarrow \widetilde{E1}_{ij}=\tilde{A}_k$;

(b) $r\left(\widetilde{E1}_{ij},\tilde{A}_k\right)=r\left(\tilde{A}_k,\tilde{B}_{ij}\right)$;

(c) $r\left(\widetilde{E1}_{ij},\tilde{A}_k\right)\le r\left(\widetilde{E1}_{ij},\tilde{C}\right)+r\left(\tilde{C},\tilde{A}_k\right)$, $\tilde{C}$ is a fuzzy set defined on the interval [-1, 1].

The relationship between all the λ $(=30)$ possible types of body shapes and the j-th basic style element D_j can be expressed by a (λ×3)-dimensional fuzzy relational matrix $R\left(BS,D_j\right)$.

$$R\left(BS,D_j\right)=\begin{pmatrix} r\left(\widetilde{E1}_{1j},\tilde{A}_1\right) & r\left(\widetilde{E1}_{1j},\tilde{A}_2\right) & r\left(\widetilde{E1}_{1j},\tilde{A}_3\right)\\ r\left(\widetilde{E1}_{2j},\tilde{A}_1\right) & r\left(\widetilde{E1}_{2j},\tilde{A}_2\right) & r\left(\widetilde{E1}_{2j},\tilde{A}_3\right)\\ \vdots & \vdots & \vdots\\ r\left(\widetilde{E1}_{\lambda j},\tilde{A}_1\right) & r\left(\widetilde{E1}_{\lambda j},\tilde{A}_2\right) & r\left(\widetilde{E1}_{\lambda j},\tilde{A}_3\right)\end{pmatrix}\quad (j=1,2,\dots,K_1) \tag{4-19}$$

where K_1 is the total number of all basic style elements.

The relational matrix $R(bs,D_j)$ of the j-the basic style element to a specific body shape bs can be obtained by using the composition operation of the (6× λ)-dimensional body shape matrix $BODY$ (see Section 2.5.1) and $R(BS,D_j)$, i.e.

$$R\left(bs,D_j\right)=BODY\circ R\left(BS,D_j\right) \tag{4-20}$$

The elements of the (6×3)-dimensional fuzzy matrix $R\left(bs,D_j\right)$ represent the close degree of a specific basic style element D_j related to a specific body shape bs at the six body positions. It is necessary to set up a data fusion model for obtaining the overall relevancy of D_j to bs and making recommendations according to the results of the overall relevancy for all the basic styles.

4.2.3 Data fusion model for aggregating all the body positions

For each basic style component (i.e. one of Pattern, Waist-Level and Leg-Opening-Level) or set of basic style elements, the importance values of different body positions (waist, hip, abdomen, leg, thigh and calf) are quite different from another basic style component. It is for this reason that we define the corresponding weights.

Let w_{ik} be the weight (importance) of the i-th body position $(i\in\{1,2,\dots,6\})$ to the k-th basic style component ($k \in \{1, 2, 3\}$). For each basic style component, we have the weight vector

$$W^{(k)} = (w_{1k}, w_{2k}, w_{3k}, w_{4k}, w_{5k}, w_{6k}) \quad (k = 1, 2, 3) \tag{4-21}$$

where $w_{1k} + w_{2k} + w_{3k} + w_{4k} + w_{5k} + w_{6k} = 1$.

For a specific body shape bs, the fuzzy comprehensive evaluation vector $EV^{(j)}$ of the j-th basic style element D_j is

$$EV^{(j)} = W^{(k)} \circ R(bs, D_j) \tag{4-22}$$

where $k = 1$ if $j \in \{1, .., k_1\}$ (k_1 is the total number of the Pattern elements), $k = 2$ if $j \in \{k_1 + 1, \dots, k_2\}$ (k_2 is the total number of the Waist-Level elements), $k = 3$ if $j \in \{k_2 + 1, \dots, k_3\}$ (k_3 is the total number of the Leg-Opening-Level elements).

Next, we normalize the vector $EV^{(j)}$ to be

$$EV_0^{(j)} = \left(ev_1^{(j)},\ ev_2^{(j)},\ ev_3^{(j)}\right) \tag{4-23}$$

Let $num(\tilde{A}_1) = -1$, $num(\tilde{A}_2) = 0$ and $num(\tilde{A}_3) = 1$ be the equivalence values of the fuzzy values $\tilde{A}_1$ (unfit), $\tilde{A}_2$ (neutral) and $\tilde{A}_3$ (fit), and the equivalence vector is denoted by

$$L = \left(num(\tilde{A}_1),\ num(\tilde{A}_2),\ num(\tilde{A}_3)\right) \tag{4-24}$$

We define the overall relevancy degree of the j-th basic style element D_j to a specific body shape bs, as follows.

$$\rho(bs, D_j) = \sum_{k=1}^{3} \left(ev_k^{(j)} \cdot num(\tilde{A}_k)\right) \triangleq \rho_j \quad (j = 1, 2 \dots, K_1) \tag{4-25}$$

In general, different designers pay their attentions on different basic style components according to their personalized experiences. In this context, we define a weight vector $\omega = (\omega_1, \omega_2, \omega_3)$, where ω_i $(i = 1,2,3)$ is the weight of a designer to the i-th style component.

As each basic style s_1 is composed of only three elements belonging to the pattern style component, waist style component and leg opening style component respectively, we denote it by a 3-dimensional vector, i.e. $s_1 = (PATTERN_x,\ WAIST_y,\ LEG_z)$ $(PATTERN_x \in PATTERN,$
$WAIST_y \in WAIST, LEG_z \in LEG)$, whose relevancy degrees of these three style components corresponding to the body shape bs can be computed by $\rho_{s_1} = (\rho_x,\ \rho_{y+k_1},\ \rho_{z+k_1+k_2})$. We define the relevancy degree of the basic style s_1 to the body shape bs from the computation on ρ_{s_1} :

$$f(x,y,z) = \omega \circ \rho_{s_1} \tag{4-26}$$

where $x \in \{1,2,\ldots,k_1\}, y \in \{1,2,\ldots,k_2\}, z \in \{1,2,\ldots,k_3\}$, with $\omega_1 + \omega_2 + \omega_3 = 1$.

Also, for controlling the values of $f(x,y,z)$ to some limits (neither too big nor too small), we define an adjustment coefficient $c_0 = 1/\max\{f(x,y,z)\}$, and then modify the relevancy degree $f(x,y,z)$ of a basic style s_1 related to a specific body shape bs as follows.

$$f_{xyz} = c_0 \cdot f(x,y,z) \tag{4-27}$$

According to the above computation, we can characterize the relations between all the possible lower body shapes defined in Section 2.5.1 and all the possible basic styles.

4.2.4 Basic styles recommendation for a specific body shape

Given a threshold Td, according to the Fuzzy Selecting Threshold Principle (Section 3.1.5.1), all the basic styles in the design styles base (see Section 2.4.2) satisfying $f_{xyz} \geq Td$ are ranked and recommended in a descending order of f_{xyz}.

According to this model, a user (designer) can obtain one or a group of ranked optimal basic design styles if she/he provides the eight key dimensions characterizing the lower body of a consumer.

4.2.5 An illustrative example

Taking body_1 of Section 4.1.3 as example, we give the style recommendation process for this special body shape. For simplicity, we consider that the preferences on the three design style components are the same, i.e. $\omega_i = 1/3\ (i = 1, 2, 3)$.

(1) Weights of the body positions related to each basic style component

These weights can be identified by using the AHP method. According to the comparisons between the six different body positions related to each specific basic style component, we obtain the following three judgment matrices:

$$J_{\text{pattern}} = \begin{array}{c} \begin{matrix} \text{waist} & \text{hip} & \text{abdomen} & \text{leg} & \text{thigh} & \text{calf} \end{matrix} \\ \begin{pmatrix} 1 & 1/3 & 1/5 & 5 & 1/7 & 3 \\ 3 & 1 & 1/3 & 7 & 1/5 & 5 \\ 5 & 3 & 1 & 8 & 1/3 & 7 \\ 1/5 & 1/7 & 1/8 & 1 & 1/9 & 1/3 \\ 7 & 5 & 3 & 9 & 1 & 8 \\ 1/3 & 1/5 & 1/7 & 3 & 1/8 & 1 \end{pmatrix} \end{array} \begin{matrix} \text{waist} \\ \text{hip} \\ \text{abdomen} \\ \text{leg} \\ \text{thigh} \\ \text{calf} \end{matrix}$$

$$J_{\text{waist-level}} = \begin{array}{c} \begin{matrix} \text{waist} & \text{hip} & \text{abdomen} & \text{leg} & \text{thigh} & \text{calf} \end{matrix} \\ \begin{pmatrix} 1 & 3 & 1/3 & 1/5 & 5 & 7 \\ 1/3 & 1 & 1/5 & 1/7 & 3 & 5 \\ 3 & 5 & 1 & 1/3 & 7 & 8 \\ 5 & 7 & 3 & 1 & 8 & 9 \\ 1/5 & 1/3 & 1/7 & 1/8 & 1 & 3 \\ 1/7 & 1/5 & 1/8 & 1/9 & 1/3 & 1 \end{pmatrix} \end{array} \begin{matrix} \text{waist} \\ \text{hip} \\ \text{abdomen} \\ \text{leg} \\ \text{thigh} \\ \text{calf} \end{matrix}$$

$$J_{\text{leg-opening-level}} = \begin{array}{c} \begin{matrix} \text{waist} & \text{hip} & \text{abdomen} & \text{leg} & \text{thigh} & \text{calf} \end{matrix} \\ \begin{pmatrix} 1 & 1/5 & 1/3 & 1/7 & 1/9 & 1/8 \\ 5 & 1 & 3 & 1/3 & 1/7 & 1/5 \\ 3 & 1/3 & 1 & 1/5 & 1/8 & 1/7 \\ 7 & 3 & 5 & 1 & 1/5 & 1/3 \\ 9 & 7 & 8 & 5 & 1 & 3 \\ 8 & 5 & 7 & 3 & 1/3 & 1 \end{pmatrix} \end{array} \begin{matrix} \text{waist} \\ \text{hip} \\ \text{abdomen} \\ \text{leg} \\ \text{thigh} \\ \text{calf} \end{matrix}$$

From these matrices, we obtain the following results:

The maximum eigenvalue of J_{pattern} is $\lambda_{max}(J_{\text{pattern}}) = 6.4803$ and the corresponding eigenvector is $W_{\text{pattern}} = (\overset{\text{waist}}{0.1332}, \overset{\text{hip}}{0.2530}, \overset{\text{abdomen}}{0.4663}, \overset{\text{leg}}{0.0434}, \overset{\text{thigh}}{0.8329}, \overset{\text{calf}}{0.0722})$. Next, the consistency of the data in the matrix J_{pattern} is validated by computing the average random consistency index $RI_{\text{pattern}} = 1.24$ $(n = 6)$ and the consistency index $CI_{\text{pattern}} = (\lambda_{max}(J_{\text{pattern}}) - 6)/5 = 0.09606$. As the random consistency rate $CR_{\text{pattern}} = CI_{\text{pattern}}/RI_{\text{pattern}} = 0.07747 < 0.1$, the judgment matrix J_{pattern} can be acceptable.

The weight vector $W^{(\text{pattern})}$ is the normalized eigenvector of W_{pattern}, i.e.

$$W^{(\text{pattern})} = (\overset{\text{waist}}{0.0740}, \overset{\text{hip}}{0.1405}, \overset{\text{abdomen}}{0.2589}, \overset{\text{leg}}{0.0241}, \overset{\text{thigh}}{0.4625}, \overset{\text{calf}}{0.0401})$$

According to the same procedure, we can find that both $J_{\text{waist-level}}$ and $J_{\text{leg-opening-level}}$ can be validated by the consistency test. The corresponding normalized weight vectors are:

$$W^{(\text{waist-level})} = (\overset{\text{waist}}{0.1405}, \overset{\text{hip}}{0.0740}, \overset{\text{abdomen}}{0.2589}, \overset{\text{leg}}{0.4625}, \overset{\text{thigh}}{0.0401}, \overset{\text{calf}}{0.0241})$$

$$W^{(\text{leg-opening-level})} = (\overset{\text{waist}}{0.0241}, \overset{\text{hip}}{0.0740}, \overset{\text{abdomen}}{0.0401}, \overset{\text{leg}}{0.1405}, \overset{\text{thigh}}{0.4625}, \overset{\text{calf}}{0.2589})$$

(2) Computation of the close degree of the basic design styles to a specific body shape

For body_1 (as denoted as bs^*), the body shape matrix (see Section 2.5.2) is

$$BODY = \begin{pmatrix} ws^* & 0 & 0 & 0 & 0 & 0 \\ 0 & hs^* & 0 & 0 & 0 & 0 \\ 0 & 0 & as^* & 0 & 0 & 0 \\ 0 & 0 & 0 & ll^* & 0 & 0 \\ 0 & 0 & 0 & 0 & ts^* & 0 \\ 0 & 0 & 0 & 0 & 0 & cs^* \end{pmatrix}_{6\times30}$$

where ws^*, hs^*, as^*, ll^*, ts^* and cs^* are the waist shape vector, the hip shape vector, the abdomen shape vector, the leg length vector, the thigh shape vector and the calf shape vector of the body shape $bs^* = \left(WS^{(S)},\ HS^{(M)},\ AS^{(M)},\ LL^{(S)},\ TS^{(M)},\ CS^{(M)}\right)$, and $ws^* = (0,1,0,0,0)$, $hs^* = as^* = ll^* = ts^* = cs^* = (0,0,1,0,0)$.

Next, we calculate the relational matrix $R(BS, D_j)$ (relations between all the possible body shapes in BS and the j-th basic style element) using the Equation (4-18).

Thus, the relational matrix $R(bs^*, D_j)$ of the j-th basic style element D_j to body_1 (bs^*) is $R\left(bs^*, D_j\right) = BODY \circ R\left(BS, D_j\right)$

$$= \begin{pmatrix} r\left(\widetilde{E1}_{2j}, \tilde{A}_1\right) & r\left(\widetilde{E1}_{2j}, \tilde{A}_2\right) & r\left(\widetilde{E1}_{2j}, \tilde{A}_3\right) \\ r\left(\widetilde{E1}_{8j}, \tilde{A}_1\right) & r\left(\widetilde{E1}_{8j}, \tilde{A}_2\right) & r\left(\widetilde{E1}_{8j}, \tilde{A}_3\right) \\ r\left(\widetilde{E1}_{13,j}, \tilde{A}_1\right) & r\left(\widetilde{E1}_{13,j}, \tilde{A}_2\right) & r\left(\widetilde{E1}_{13,j}, \tilde{A}_3\right) \\ r\left(\widetilde{E1}_{18,j}, \tilde{A}_1\right) & r\left(\widetilde{E1}_{18,j}, \tilde{A}_2\right) & r\left(\widetilde{E1}_{18,j}, \tilde{A}_3\right) \\ r\left(\widetilde{E1}_{23,j}, \tilde{A}_1\right) & r\left(\widetilde{E1}_{23,j}, \tilde{A}_2\right) & r\left(\widetilde{E1}_{23,j}, \tilde{A}_3\right) \\ r\left(\widetilde{E1}_{28,j}, \tilde{A}_1\right) & r\left(\widetilde{E1}_{28,j}, \tilde{A}_2\right) & r\left(\widetilde{E1}_{28,j}, \tilde{A}_3\right) \end{pmatrix} \begin{matrix} \text{waist: the 2nd of } ws^* \text{ is not null} \\ \text{hip: the 3rd of } hs^* \text{ is not null} \\ \text{abdomen: the 3rd of } as^* \text{ is not null} \\ \text{leg: the 3rd of } ll^* \text{ is not null} \\ \text{thigh: the 3rd of } ws^* \text{ is not null} \\ \text{calf: the 3rd of } ws^* \text{ is not null} \end{matrix}$$

e.g.

$$R(bs^*, D_1) = \begin{pmatrix} 0.2421 & 0.5615 & 0.7995 \\ 0.5006 & 0.8943 & 0.3972 \\ 0.3972 & 0.7147 & 0.3139 \\ 0.3972 & 0.8943 & 0.5006 \\ 0.3139 & 0.7147 & 0.3972 \\ 0.3139 & 0.7147 & 0.3972 \end{pmatrix},$$

$$R(bs^*, D_2) = \begin{pmatrix} 0.2728 & 0.6284 & 0.7147 \\ 0.2139 & 0.5006 & 0.8943 \\ 0.5615 & 0.7995 & 0.3534 \\ 0.3972 & 0.8943 & 0.5006 \\ 0.3534 & 0.7995 & 0.5615 \\ 0.3972 & 0.8943 & 0.5006 \end{pmatrix}, \ldots$$

From the above results, we obtain the relevancy degree of all the basic style elements D_j $(j = 1, \ldots, 11)$ to bs^*: $\rho(bs^*, D_1) = 0.0330$, $\rho(bs^*, D_2) = 0.1045$, $\rho(bs^*, D_3) = 0.2200$, $\rho(bs^*, D_4) = 0.1223$, $\rho(bs^*, D_5) = 0.0261$, $\rho(bs^*, D_6) = 0.1625$, $\rho(bs^*, D_7) = 0.2098$, $\rho(bs^*, D_8) = 0.1352$, $\rho(bs^*, D_9) = 0.3074$, $\rho(bs^*, D_{10}) = 0.2476$, $\rho(bs^*, D_{11}) = 0.0762$.

(3) Recommendation of the basic design styles for a specific body shape (the threshold $Td = 0.9$)

The relevancy degrees of all the 48 basic design styles (combinations of all style elements in Pattern (4 elements), Waist Level (3 elements) and Leg Opening Level (4 elements)) in the design styles base to body_1 (bs^*) are shown in Table 4-3.

Table 4-3 The relevancy degrees of body_1 to all the basic styles

Basic style	Relevancy degree	Basic style	Relevancy degree	Basic style	function value	Relevancy degree	function value
$(1,1,1)$	0.2636	$(1,1,2)$	0.4972	$(1,1,3)$	0.4160	$(1,1,4)$	0.1836
$(1,2,1)$	0.4486	$(1,2,2)$	0.6822	$(1,2,3)$	0.6011	$(1,2,4)$	0.3686
$(1,3,1)$	0.5128	$(1,3,2)$	0.7463	$(1,3,3)$	0.6652	$(1,3,4)$	0.4327
$(1,4,1)$	0.3605	$(2,1,2)$	0.5941	$(2,1,3)$	0.5129	$(2,1,4)$	0.2805
$(2,2,1)$	0.5455	$(2,2,2)$	0.7791	$(2,2,3)$	0.6980	$(2,2,4)$	0.4655
$(2,3,1)$	0.6097	$(2,3,2)$	0.8432	$(2,3,3)$	0.7621	$(2,3,4)$	0.5296
$(3,1,1)$	0.5173	$(3,1,2)$	0.7508	$(3,1,3)$	0.6697	$(3,1,4)$	0.4373
$(3,2,1)$	0.7023	$(\mathbf{3},\mathbf{2},\mathbf{2})$	**0.9359**	$(3,2,3)$	0.8547	$(3,2,4)$	0.6223
$(3,3,1)$	0.7665	$(\mathbf{3},\mathbf{3},\mathbf{2})$	**1**	$(\mathbf{3},\mathbf{3},\mathbf{3})$	**0.9189**	$(3,3,4)$	0.6277
$(4,1,1)$	0.3848	$(4,1,2)$	0.6183	$(4,1,3)$	0.5372	$(4,1,4)$	0.3047
$(4,2,1)$	0.5698	$(4,2,2)$	0.8033	$(4,2,3)$	0.7222	$(4,2,4)$	0.4776
$(4,3,1)$	0.6339	$(4,3,2)$	0.8675	$(4,3,3)$	0.7863	$(4,3,4)$	0.5539

In Table 4-3, the basic design styles satisfying $f_{xyz} \geq 0.9$ are $s_1^{(1)} = (PATTERN_3, WAIST_3, LEG_2)$, $s_1^{(2)} = (PATTERN_3, WAIST_2, LEG_2)$ and $s_1^{(3)} = (PATTERN_3, WAIST_3, LEG_3)$ and the optimal design style is $s_1^{(1)}$ with the maximal relevancy degree. All of the three basic design styles are taken as recommendation results for body_1.

4.2.6 Validation of the model

According to the modular design of garment, 48 basic design styles in the design styles base are regarded as references. For every human body shape, the model proposed in Section 4.2.5 can rank all the reference styles and select the best one as recommended solution. In order to validate the effectiveness of the model, we invite 12 panelists in Group 1 (6 garment designers, see Section 2.4.1) and Group 2 (6 pattern designers, see Section 2.4.1) to select the most suitable style for each of the 103 3D virtual body shapes identified in Section 4.1. For simplicity, in each evaluation performed by all the panelists, the most selected style is taken as the final result.

The comparison between the outputs of the model and expert evaluation results for different body shapes on three components of basic design styles is shown in Figure 4-13.

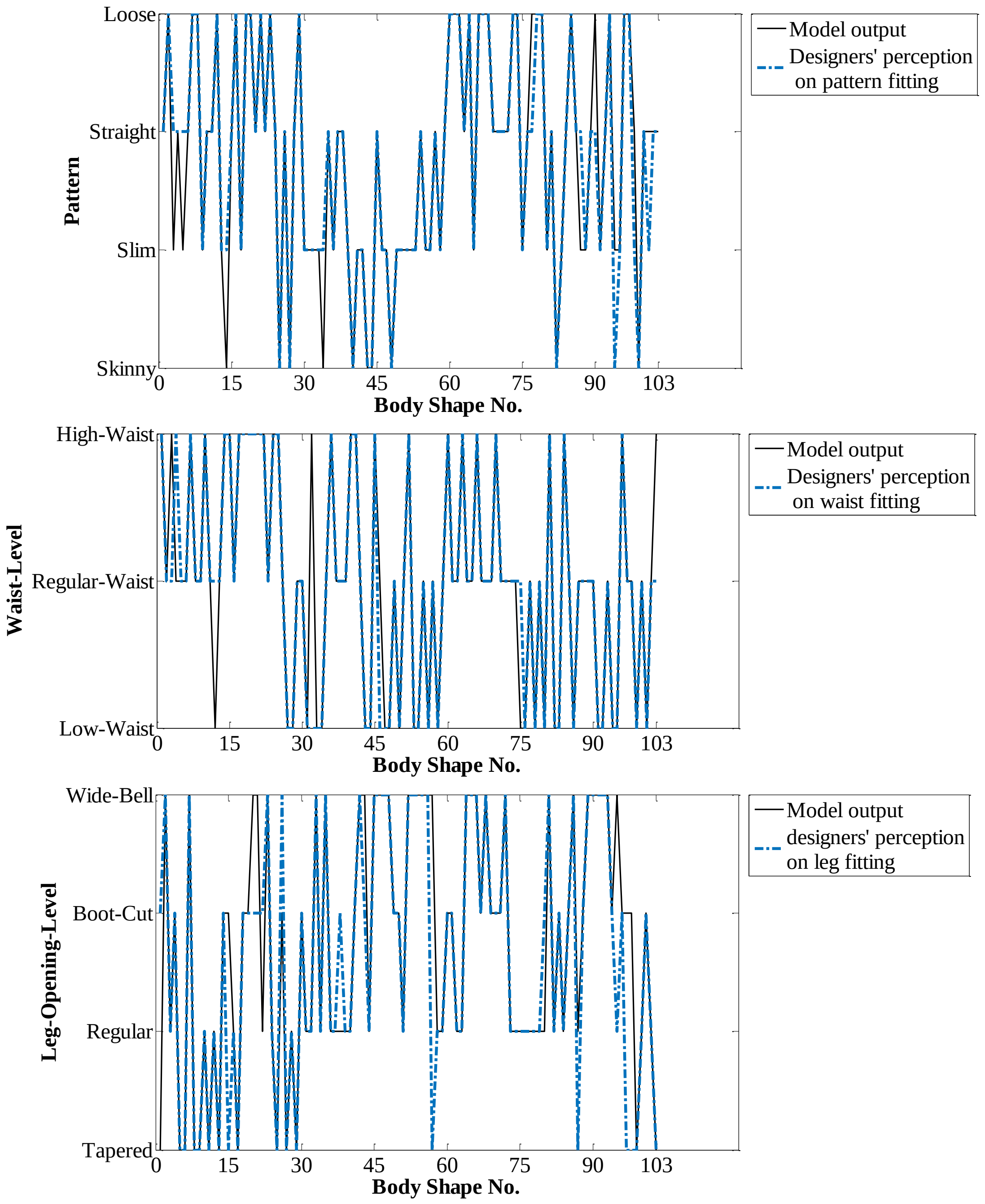


Figure 4-13 Comparison between output results of the model and designers' perception on basic style design

The values of Model_Error of each basic style component are listed in Table 4-4.

Table 4-4 The Model Error of the basic style components

	Pattern	Waist-Level	Leg-Opening-Level
Model_Error	0.3116	0.3116	0.5994

From the above results, it can be seen that the proposed model can effectively acquire knowledge since all the values of Model_Error do not exceed 0.6. In fact, the error of Pattern fitting is lower than 0.4 level of 4 (<10%), the error of Waist-Level fitting is lower than 0.4 level of 3 (<14%), and the error of Leg-Opening-Level fitting is lower than 0.6 level of 4 (<15%) in average.

4.3 Modeling the relationship between Fashion Themes and Design Styles (Model 3)

In this Section, we set up the relational model between fashion themes and design styles by using fuzzy techniques. The flow diagram of Model 3 is shown in Figure 4-14 and the details of modeling are given in the following Section.

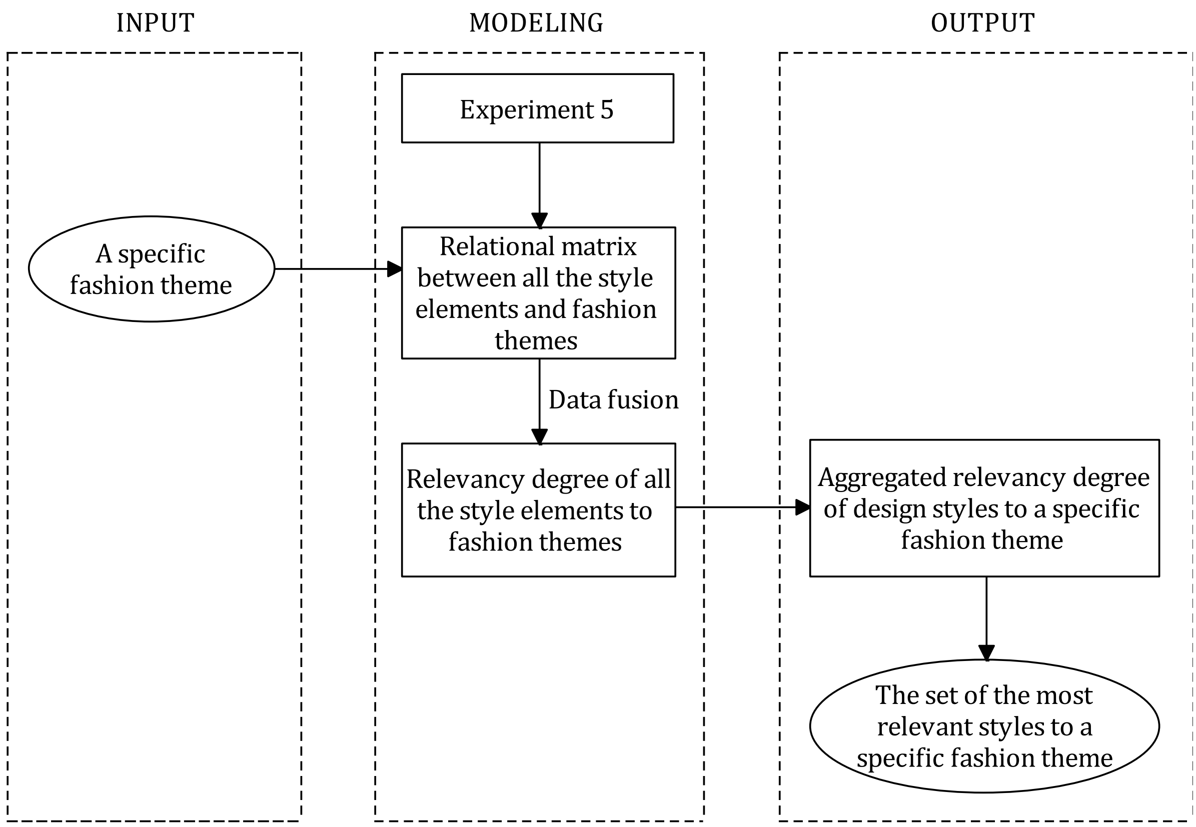


Figure 4-14 Functional Structure of Model 3

Having obtained experts' evaluation scores from the Experiment 5 in Chapter 2, we use the fuzzy technique to model the relationship between the fashion themes and the style elements.

4.3.1 Formulization of the linguistic evaluation scores for fashion themes

For each fashion theme and each style element, the evaluation score characterizing their relevancy come from the set of seven linguistic levels (scores), respectively expressed by the fuzzy sets $\tilde{F}_1, \tilde{F}_2, \tilde{F}_3, \tilde{F}_4, \tilde{F}_5, \tilde{F}_6, \tilde{F}_7$, having the property of "bilateral symmetry and middle value is higher than bilateral ones". Assume these seven levels be quantitatively represented by "-3", "-2", "-1", "0", "1", "2" and "3". These seven fuzzy sets can be regarded as the standard evaluation levels, whose membership functions are expressed by the triangular functions defined on interval $[-3, 3]$ as follows.

$$\mu_{\tilde{F}_k}(x) = \begin{cases} x - k + 1, & \text{if } \max\{-3, k-1\} \le x \le k \\ -x + k + 1, & \text{if } k \le x \le \min\{3, k+1\} \\ 0, & \text{otherwise} \end{cases} \quad (-3 \le x \le 3)\ (k = 1,2,\dots,7) \quad (4\text{-}28)$$

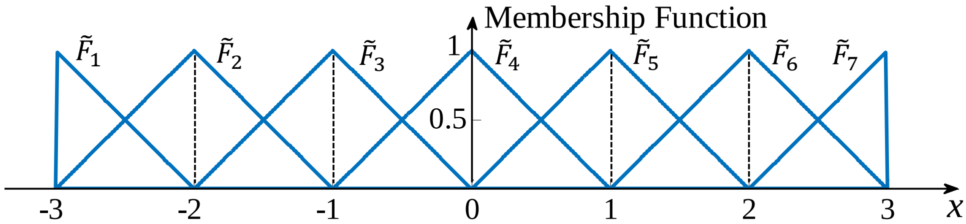


Figure 4-15 The membership functions of evaluation scores on relevancy of style elements to fashion themes

We assume that $r2_{ij}^{(k)}$ represents the number of people among the r panelists who give the evaluation score k $(k \in \{-3, -2, -1, 0, 1, 2, 3\})$ on the relevancy of the i-th $(i \in \{1, \dots, K\})$ style element (All the K possible style elements have been defined in Table 2-5 with $K = K_1$ (number of basic style elements) $+ k_4$ (number if detail elements) $+ k_5$ (number of accessories) to the j-th $(j \in \{1, \dots, t\})$ fashion theme (The set of all the t fashion themes is $T = \{\underbrace{\text{Neuter-Feminine}}_{T_1}, \underbrace{\text{Elegant-Wild}}_{T_2}, \underbrace{\text{Traditional-Modern}}_{T_3}\}$) with $t = 3$. The symbols have been defined in Section 2.5.2.

The evaluation results of all the panelists can be expressed by a fuzzy distribution:

$$\widetilde{E2}_{ij} = \left(\frac{r2_{ij}^{(-3)}}{r}, \frac{r2_{ij}^{(-2)}}{r}, \frac{r2_{ij}^{(-1)}}{r}, \frac{r2_{ij}^{(0)}}{r}, \frac{r2_{ij}^{(1)}}{r}, \frac{r2_{ij}^{(2)}}{r}, \frac{r2_{ij}^{(3)}}{r} \right)$$

$$= \left(e2_{ij}^{(-3)}, e2_{ij}^{(-2)}, e2_{ij}^{(-1)}, e2_{ij}^{(0)}, e2_{ij}^{(1)}, e2_{ij}^{(2)}, e2_{ij}^{(3)} \right) \quad (4\text{-}29)$$

$\widetilde{E2}_{ij}$ is a fuzzy set, whose membership function $\mu_{\widetilde{E2}_{ij}}(x)$ is a triangle or polygonal function which takes points $(-3, 0)$, $(-3, e2_{ij}^{(-3)})$, $(-2, e2_{ij}^{(-2)})$, $(-1, e2_{ij}^{(-1)})$, $(0, e2_{ij}^{(0)})$, $(1, e2_{ij}^{(1)})$, $(2, e2_{ij}^{(2)})$, $(3, e2_{ij}^{(3)})$ and $(3, 0)$ as vertexes (some points could be coincident). A

$\mu_{\widetilde{E2}_{ij}}(x)$

general membership function of the evaluation results is given in Figure 4-15.

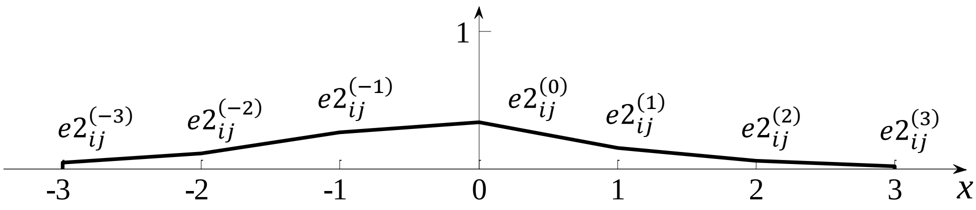


Figure 4-16 A general fuzzy membership function of the evaluation results

4.3.2 Relevancy between fashion themes and style elements

We define the *Close Degree* of the aggregated evaluation result for all the r panelists on the i-th style element related to the j-th fashion theme (T_j), denoted as $r\left(\widetilde{E2}_{ij}, \tilde{F}_k\right)$, to the standard evaluation level (score) $\tilde{F}_k$ according to the Equation (4-30).

$$r\left(\widetilde{E2}_{ij}, \tilde{F}_k\right) = \frac{\int_{-3}^{3}\left[\mu_{\widetilde{E2}_{ij}}(x) \wedge \mu_{\tilde{F}_k}(x)\right]dx}{\int_{-3}^{3}\left[\mu_{\widetilde{E2}_{ij}}(x) \vee \mu_{\tilde{F}_k}(x)\right]dx} \quad (i = 1, \dots, K;\ j = 1, \dots, t;\ k = 1, \dots, 7) \qquad (4\text{-}30)$$

The (K×7)-dimensional relational matrix of all the style elements related to the fashion theme T_j for all the evaluation levels is defined by

$$R(S, T_j) = \begin{pmatrix} r\left(\widetilde{E2}_{1j}, \tilde{F}_1\right) & r\left(\widetilde{E2}_{1j}, \tilde{F}_2\right) & \cdots & r\left(\widetilde{E2}_{1j}, \tilde{F}_7\right) \\ r\left(\widetilde{E2}_{2j}, \tilde{F}_1\right) & r\left(\widetilde{E2}_{2j}, \tilde{F}_2\right) & \cdots & r\left(\widetilde{E2}_{2j}, \tilde{F}_7\right) \\ \vdots & \vdots & \ddots & \vdots \\ r\left(\widetilde{E2}_{Kj}, \tilde{F}_1\right) & r\left(\widetilde{E2}_{Kj}, \tilde{F}_2\right) & \cdots & r\left(\widetilde{E2}_{Kj}, \tilde{F}_7\right) \end{pmatrix} \quad (j = 1,2, \dots, t) \qquad (4\text{-}31)$$

The relational matrix $R(s, T_j)$ of a specific style s related to the fashion theme T_j is defined by the composition operation of the style matrix $STYLE$ (see Section 2.5.2) and $R(S, T_j)$, i.e.

$$R(s, T_j) = STYLE \circ R(S, T_j) \quad (j = 1,2, \dots, t) \qquad (4\text{-}32)$$

Assume the weight of the style element D_i be ω_i $(i = 1,2, \dots, \mu)$, where the weight vector $\omega = (\omega_1, \omega_2, \dots, \omega_\mu)$ and μ is the total number of all style elements in the specific style s.

The *relevancy degree* of a specific style s to the k-th evaluation level of the fashion theme T_j is defined by

$$\rho\left(s, T_j^{(k)}\right) = \omega \circ R(s, T_j)^{(k)} \qquad (4\text{-}33)$$

where $T_j^{(k)}$ expresses the k-th evaluation level of the fashion theme T_j and $R(s, T_j)^{(k)}$ the k-th column vector of $R(s, T_j)$ $(k \in \{1,2, \dots, 7\})$.

Thus, we obtain the distribution of the relevancy degrees of a specific style s related to the fashion theme T_j for all the evaluation levels as follows.

$$ST^{(j)} = \left(\frac{\rho\left(s, T_j^{(1)}\right)}{\sum_{k=1}^{7} \rho\left(s, T_j^{(k)}\right)}, \frac{\rho\left(s, T_j^{(2)}\right)}{\sum_{k=1}^{7} \rho\left(s, T_j^{(k)}\right)}, \dots, \frac{\rho\left(s, T_j^{(7)}\right)}{\sum_{k=1}^{7} \rho\left(s, T_j^{(k)}\right)} \right) \tag{4-34}$$

Thus, we can compute the relevancy degrees of all the styles related to the 7 evaluation levels of all the fashion themes.

4.3.3 Identification of style sets related to fashion themes

According to the Fuzzy Selecting Near Principle (Section 3.1.5.2), for the fashion theme T_j, s is the most relevant style to the k^*-th evaluation level of the fashion theme T_j, if

$$\rho\left(s, T_j^{(k^*)}\right) = \bigvee_{k=1}^{7} \{\rho\left(s, T_j^{(k)}\right)\} \tag{4-35}$$

For a given evaluation level (k^*-th level) of the fashion theme T_j, all the styles satisfying (4-34) (i.e. their distributions of relevancy degrees related to T_j reach the maximums at the k^*-th evaluation level) constitute the set of styles $S_{k^*}^{(j)}$.

If there are multiple peak values in the distribution $ST^{(j)}$, it means that the evaluators have some conflicts between them on the choice of evaluations levels and then the corresponding relevancy degrees become more uncertain. In this case, some non-empty interactions exist between $S_{k^*}^{(j)}$'s for different values of k^*. The number of styles included in these interactions represents the level of uncertainty during the evaluation.

If $S_{k^*}^{(j)}$ is an empty set, we consider that no style is relevant to the k^*-th evaluation level of the fashion theme T_j. It means that the user's requirement on k^*-th evaluation level is not reasonable and no existing style corresponds to this evaluation level for the specific fashion theme. In this case, we will ask the user to adjust his/her requirement so that feasible design solutions can be generated. For example, if one designer initially requires "Very Elegant" for the new design but there is no style in the base corresponding to this requirement, then the system will ask him/her to give another choice from the evaluation levels "a little Elegant" and "Elegant", both corresponding to non-empty sets of styles.

It is possible that a user requires a style satisfying to several fashion themes. In this case, we just take the intersection of the sets of styles corresponding to these fashion themes as the final set of styles.

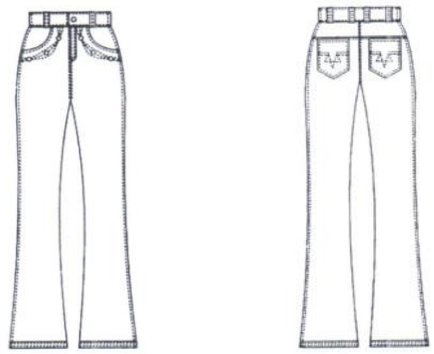
Moreover, for a new style, we can also suggest to which evaluation level of relevancy it belongs for a specific fashion theme. In practice, the base of styles is an open structure and permits to integrate more and more new styles by designers. With introduction of more styles, the recommendation results will become more reasonable. However, in the specific case of jeans design, the styles in our current base, i.e. the combinations of all style elements shown in Table2-5, are enough for dealing with all kinds of requirements.

4.3.4 An illustrative example

We consider the fashion theme T_2 (*Elegant*-*Wild*) and a specific style

$s = (\overset{PATTERN_3}{\text{Straight}},\ \overset{WAIST_2}{\text{Regular-Waist}},\ \overset{LEG_3}{\text{Boot-Cut}},\ \overset{DETAIL_{11}}{\text{Crescent}},\ \overset{DETAIL_{21}}{\text{Uncovered back-pocket}},$

$\overset{DETAIL_{31}}{\text{Front-pocket with}}\ DETAIL_{41} DETAIL_{51} DETAIL_{61}$ with the number of style elements $\mu = 10$



(a) Front (b) Back

Figure 4-17 The sketch of a jeans style

In this example of personalized jean design, we only take a_2 (Embroidery) as style element but do not consider its exact location and number in the garment.

According to the proposed model, we can obtain the $(\mu \times 7)$-dimensional relational matrix $R(s, T_2)$ of the specific style s to the fashion theme T_2 (Elegant-Wild) is

$$R(s,T_2)=\begin{pmatrix} r(\widetilde{E2}_{32},\tilde{F}_1) & r(\widetilde{E2}_{32},\tilde{F}_2) & \cdots & r(\widetilde{E2}_{32},\tilde{F}_7) \\ r(\widetilde{E2}_{62},\tilde{F}_1) & r(\widetilde{E2}_{62},\tilde{F}_2) & \cdots & r(\widetilde{E2}_{62},\tilde{F}_7) \\ r(\widetilde{E2}_{10,2},\tilde{F}_1) & r(\widetilde{E2}_{10,2},\tilde{F}_2) & \cdots & r(\widetilde{E2}_{10,2},\tilde{F}_7) \\ r(\widetilde{E2}_{12,2},\tilde{F}_1) & r(\widetilde{E2}_{12,2},\tilde{F}_2) & \cdots & r(\widetilde{E2}_{12,2},\tilde{F}_7) \\ r(\widetilde{E2}_{14,2},\tilde{F}_1) & r(\widetilde{E2}_{14,2},\tilde{F}_2) & \cdots & r(\widetilde{E2}_{14,2},\tilde{F}_7) \\ r(\widetilde{E2}_{16,2},\tilde{F}_1) & r(\widetilde{E2}_{16,2},\tilde{F}_2) & \cdots & r(\widetilde{E2}_{16,2},\tilde{F}_7) \\ r(\widetilde{E2}_{18,2},\tilde{F}_1) & r(\widetilde{E2}_{18,2},\tilde{F}_2) & \cdots & r(\widetilde{E2}_{18,2},\tilde{F}_7) \\ r(\widetilde{E2}_{20,2},\tilde{F}_1) & r(\widetilde{E2}_{20,2},\tilde{F}_2) & \cdots & r(\widetilde{E2}_{20,2},\tilde{F}_7) \\ r(\widetilde{E2}_{22,2},\tilde{F}_1) & r(\widetilde{E2}_{22,2},\tilde{F}_2) & \cdots & r(\widetilde{E2}_{22,2},\tilde{F}_7) \\ r(\widetilde{E2}_{26,2},\tilde{F}_1) & r(\widetilde{E2}_{26,2},\tilde{F}_2) & \cdots & r(\widetilde{E2}_{26,2},\tilde{F}_7) \end{pmatrix}\begin{matrix} PATTERN_3 \\ WAIST_2 \\ LEG_3 \\ DETAIL_{11} \\ DETAIL_{21} \\ DETAIL_{31} \\ DETAIL_{41} \\ DETAIL_{51} \\ DETAIL_{61} \\ ACCESSORY_2 \end{matrix}$$

$$=\begin{pmatrix} 0.1011 & 0.2551 & 0.5891 & 0.7621 & 0.3358 & 0.1377 & 0.0499 \\ 0.1886 & 0.4461 & 1.0000 & 0.4461 & 0.1886 & 0.0233 & 0.0035 \\ 0.1011 & 0.2551 & 0.5891 & 0.7621 & 0.3358 & 0.1377 & 0.0499 \\ 0.1011 & 0.2551 & 0.5891 & 0.7621 & 0.3358 & 0.1377 & 0.0499 \\ 0.0499 & 0.1377 & 0.3358 & 0.7621 & 0.5891 & 0.2551 & 0.1011 \\ 0.1011 & 0.2551 & 0.5891 & 0.7621 & 0.3358 & 0.1377 & 0.0499 \\ 0.1886 & 0.4461 & 1.0000 & 0.4461 & 0.1886 & 0.0233 & 0.0035 \\ 0.0152 & 0.0499 & 0.1377 & 0.3358 & 0.7621 & 0.5891 & 0.2551 \\ 0.0038 & 0.01 & 0.0348 & 0.1011 & 0.2551 & 0.5891 & 0.7621 \\ 0.1377 & 0.3358 & 0.7621 & 0.5891 & 0.2551 & 0.1011 & 0.0348 \end{pmatrix}\begin{matrix} PATTERN_3 \\ WAIST_2 \\ LEG_3 \\ DETAIL_{11} \\ DETAIL_{21} \\ DETAIL_{31} \\ DETAIL_{41} \\ DETAIL_{51} \\ DETAIL_{61} \\ ACCESSORY_2 \end{matrix}$$

For simplicity, let $\omega_k = 1/\mu\ (k = 1,2,\dots,\mu)$. Thus, we have

$$ST^{(2)} = (\underset{\rho\left(s,T_2^{(1)}\right)}{0.0525},\ \underset{\rho\left(s,T_2^{(2)}\right)}{0.1287},\ \underset{\rho\left(s,T_2^{(3)}\right)}{0.2943},\ \underset{\rho\left(s,T_2^{(4)}\right)}{0.2709},\ \underset{\rho\left(s,T_2^{(5)}\right)}{0.1569},\ \underset{\rho\left(s,T_2^{(6)}\right)}{0.0699},\ \underset{\rho\left(s,T_2^{(7)}\right)}{0.0268})$$

Evidently, $\vee_{k=1}^{7}\{\rho\left(s,T_2^{(k)}\right)\} = \rho\left(s,T_2^{(3)}\right)$. It means that the style is relevant to the "*a little Elegant*" (the 3nd evaluation level of the theme "*Elegant−Wild*").

4.3.5 Validation of model

For testing the validity of the proposed model, we select 30 typical women's jeans of different styles from the design styles base and then generate the corresponding virtual design sketches. The panelists in Group 1 and Group 2 are invited to select the most relevant evaluation levels for each type of jeans and each of the three fashion themes by observing virtual design ketches and comparing with the results of the model. The evaluation scores come from the seven fuzzy sets $\tilde{F}_1, \tilde{F}_2, \tilde{F}_3, \tilde{F}_4, \tilde{F}_5, \tilde{F}_6, \tilde{F}_7$, which are quantitatively represented by -3, -2, -1, 0, 1, 2, 3. The ultimate results are shown in Figure 4-18.

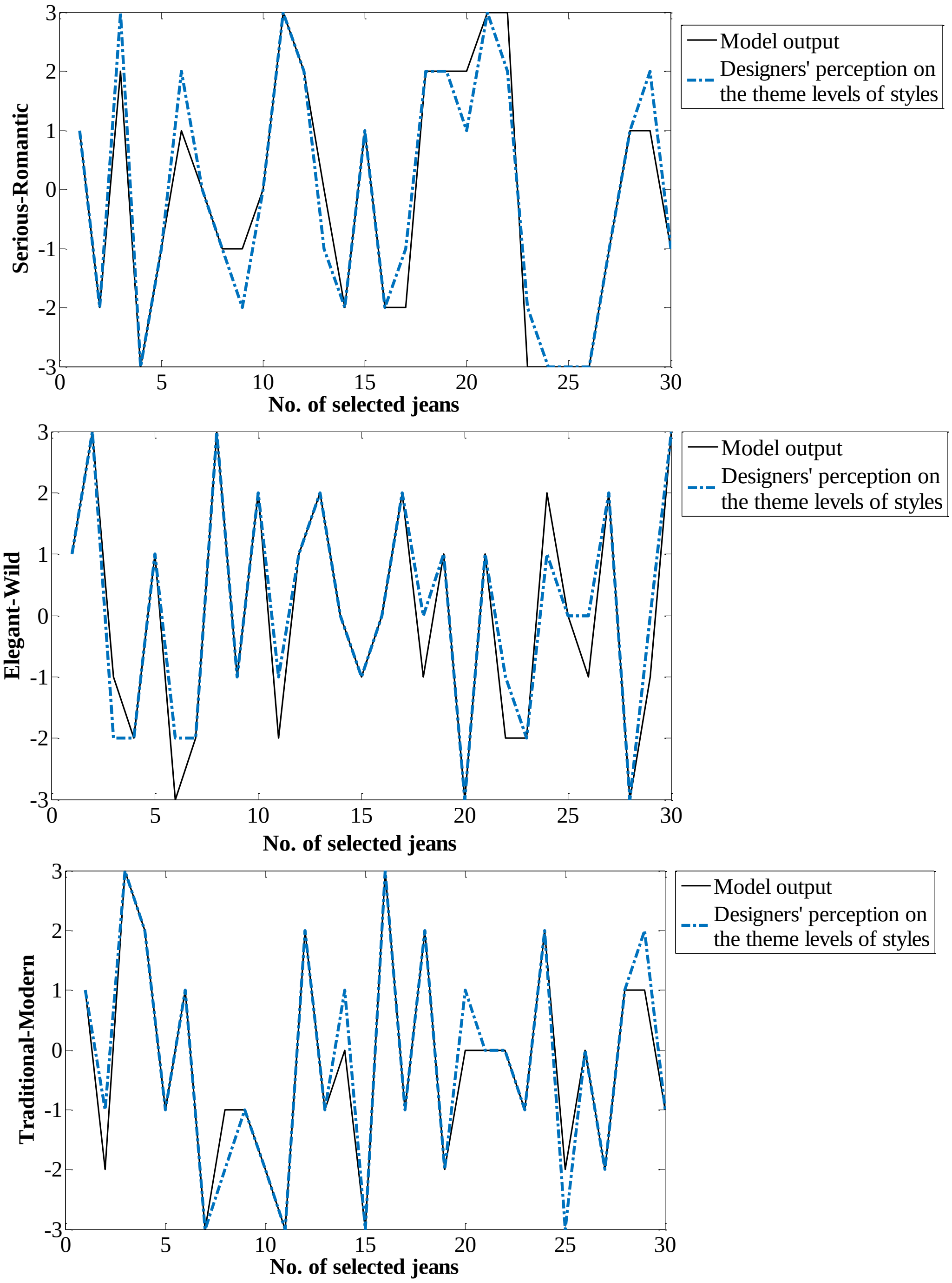


Figure 4-18 Comparison between the output results of the model and designers' perception on the relationship between fashion themes and styles

The values of Model_Error for each fashion theme related to design styles are given as follows.

Table 4-5 The Model Error of each fashion theme related to all the design styles

Fashion theme	T_1	T_2	T_3
Model_Error	0.5477	0.5164	0.4472

From Table 4-5, we can find that the proposed model is efficient since all the values of Model_Error do not exceed 0.6, i.e. the errors are all lower than 0.6 level of 7 (< 9%) in average. Therefore, the proposed model is acceptable.

4.4 Modeling the Relationship between Fashion Themes and Colors (Model 4)

In this Section, we establish the relation between fashion themes and colors by using the procedure similar to what we proposed in Section 4.3. The flow diagram of Model 4 is shown in Figure 4-19 and the details of modeling are given in the following texts.

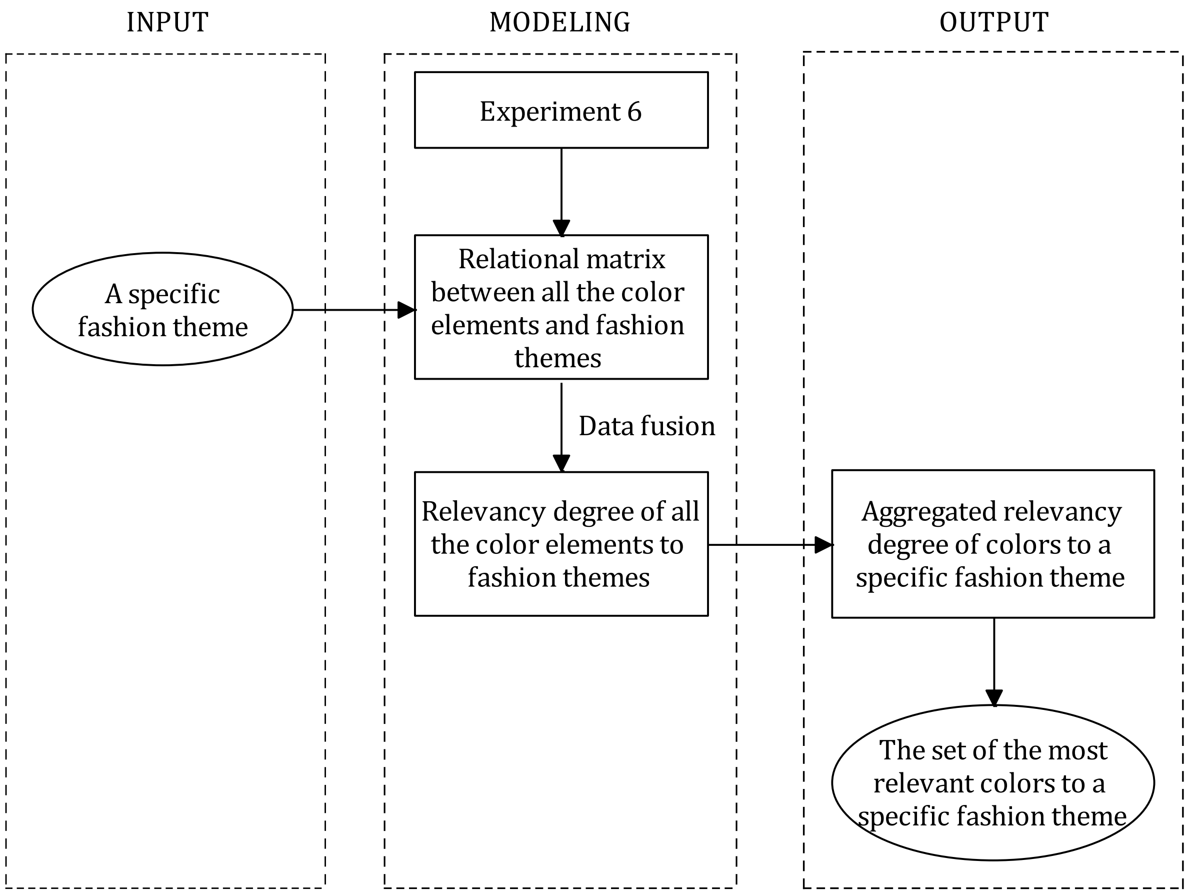


Figure 4-19 Functional Structure of Model 4

4.4.1 Formulization of the model

For each fashion theme and each color element, the evaluation scores characterizing their relevancy come from the set of seven linguistic levels (scores), respectively expressed by the fuzzy sets $\tilde{F}_1, \tilde{F}_2, \tilde{F}_3, \tilde{F}_4, \tilde{F}_5, \tilde{F}_6, \tilde{F}_7$. The membership functions of these seven fuzzy sets are shown in Equation (4-28) and Figure 4-16**.**

We assume that $r3_{ij}^{(k)}$ represents the number of people among the r panelists who give the evaluation score k $(k \in \{-3,-2,-1,0,1,2,3\})$ on the relevancy of the i-th $(i \in \{1,2,\dots,V\})$ color element (The set of all the V possible color elements is $C = \{\overset{low}{HUE_1}, \overset{middle}{HUE_2}, \overset{high}{HUE_3}, \overset{low}{VALUE_1}, \overset{middle}{VALUE_2}, \overset{high}{VALUE_3}, \overset{low}{CHROMA_1}, \overset{middle}{CHROMA_2}, \overset{high}{CHROMA_3}\}$) $(V = 9)$ to the j-th $(j \in \{1,\dots,t\})$ fashion theme (t is the total number of all the fashion themes) $(t = 3)$.

The symbols have been defined in Section 2.5.2.

The evaluation results of all the panelists can be expressed by a fuzzy distribution:

$$\widetilde{E3}_{ij} = \left(\frac{r3_{ij}^{(-3)}}{r}, \frac{r3_{ij}^{(-2)}}{r}, \frac{r3_{ij}^{(-1)}}{r}, \frac{r3_{ij}^{(0)}}{r}, \frac{r3_{ij}^{(1)}}{r}, \frac{r3_{ij}^{(2)}}{r}, \frac{r3_{ij}^{(3)}}{r}\right)$$
$$= \left(e3_{ij}^{(-3)}, e3_{ij}^{(-2)}, e3_{ij}^{(-1)}, e3_{ij}^{(0)}, e3_{ij}^{(1)}, e3_{ij}^{(2)}, e3_{ij}^{(3)}\right) \quad (4\text{-}36)$$

$\widetilde{E3}_{ij}$ is a fuzzy set, whose membership function is the same as that of $\widetilde{E2}_{ij}$.

The close degree of the fuzzy set $\widetilde{E3}_{ij}$ to the standard evaluation level (score) $\tilde{F}_k$ is similar to Equation (4-30).

The $(V\times7)$-dimensional relational matrix of all the possible color elements C to the fashion theme T_j for all the evaluation levels is defined by

$$R(C,T_j) = \left(r(\widetilde{E3}_{ij}, \tilde{F}_k)\right)_{V\times7} \quad (j = 1,2,\dots,t) \quad (4\text{-}37)$$

where V is the total number of all color elements.

The (3×7)-dimensional relational matrix $R(c,T_j)$ of a specific color c (composed of 3 color elements) to the fashion theme T_j is defined by

$$R(c,T_j) = COLAR_{3\times V} \circ R(C,T_j)_{V\times7} \quad (4\text{-}38)$$

Assume the weights of three color properties (Hue, Value and Chroma) be $\omega_1, \omega_2, \omega_3$, which constitute a weight vector $\omega = (\omega_1, \omega_2, \omega_3)$.

The *relevancy degree* of a specific color c to the k-th evaluation level of the fashion theme T_j is defined by

$$\rho\left(c, T_j^{(k)}\right) = \omega \circ R(c,T_j)^{(k)} \quad (4\text{-}39)$$

where $T_j^{(k)}$ expresses the k-th evaluation level of the fashion theme T_j and $R(c,T_j)^{(k)}$ the k-th column vector of $R(c,T_j)$ $(k \in \{1,2,\dots,7\})$.

Thus, we obtain the distribution of the relevancy degrees of a specific color c related to the fashion theme T_j for all the evaluation levels all as follows.

$$CT^{(j)} = \left(\frac{\rho\left(c, T_j^{(1)}\right)}{\sum_{k=1}^{7} \rho\left(s, T_j^{(k)}\right)}, \frac{\rho\left(c, T_j^{(2)}\right)}{\sum_{k=1}^{7} \rho\left(s, T_j^{(k)}\right)}, \dots, \frac{\rho\left(c, T_j^{(7)}\right)}{\sum_{k=1}^{7} \rho\left(s, T_j^{(k)}\right)} \right) \tag{4-40}$$

c is the most relevant color to the k^*-th evaluation level of the fashion theme T_j, if $\rho\left(c, T_j^{(k^*)}\right) = \vee_{k=1}^{7}\{\rho\left(c, T_j^{(k)}\right)\}$.

For a given evaluation level (k^*-th level) of the fashion theme T_j, all the styles satisfying the above Equation (i.e. their distributions of relevancy degrees related to T_j reach the maximums at the k^*-th evaluation level) constitute the set of colors $C_{k^*}^{(j)}$.

Similar to the discussion in Section 4.3, if several fashion themes are considered, we can obtain the most relevant set of colors for each evaluation level of a specific theme. In the same way, we just take the intersection of their corresponding sets of colors as the final set of colors.

4.4.2 An Illustrative Example

A specific vector $c = (HUE_1, VALUE_2, CHROMA_1)$ (Figure 4-20) and the theme T_2 are considered. Assume the evaluation weights given by the experts are all identical and $\omega_s = 1/3$ $(s = 1, 2, 3)$.

Figure 4-20 The denim fabric with the specific color c

(1) Computation of the close degree between fashion themes and colors

According to the results of Experiment 6, we can calculate the (9×7)-dimensional matrix $R\left(C, T_j\right)$.

(i) Computation of the (3×9)-dimensional color matrix $COLOR$

The hue vector $hue = (1, 0, 0)$, The Value vector $value = (0, 1, 0)$, and the chroma vector $chroma = (1, 0, 0)$. Thus, we can get $COLOR$.

(ii) Computation of the close degree of the specific color c to theme T_2

$$R(c,T_2)=COLOR\circ R(C,T_2)=\begin{pmatrix} r(\widetilde{E3}_{12},\tilde{F}_1) & r(\widetilde{E3}_{12},\tilde{F}_2) & \cdots & r(\widetilde{E3}_{12},\tilde{F}_7)\\ r(\widetilde{E3}_{52},\tilde{F}_1) & r(\widetilde{E3}_{52},\tilde{F}_2) & \cdots & r(\widetilde{E3}_{52},\tilde{F}_7)\\ r(\widetilde{E3}_{72},\tilde{F}_1) & r(\widetilde{E3}_{72},\tilde{F}_2) & \cdots & r(\widetilde{E3}_{72},\tilde{F}_7)\end{pmatrix}\begin{matrix} HUE_1\\ VALUE_2\\ CHROMA_1\end{matrix}$$

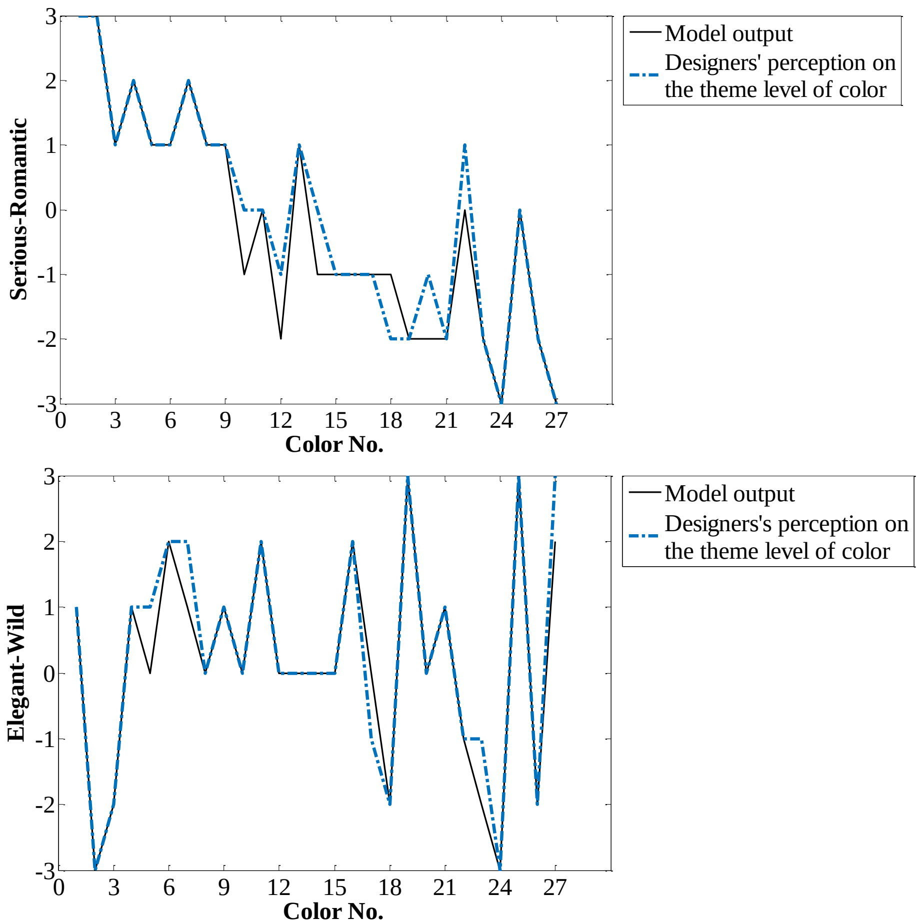
$$=\begin{pmatrix} 0.0030 & 0.1181 & 0.2357 & 0.3622 & 0.8188 & 0.5239 & 0.2929\\ 0.0062 & 0.7113 & 0.2930 & 0.6703 & 0.6703 & 0.2930 & 0.0716\\ 0.0030 & 0.1181 & 0.2929 & 0.5239 & 0.8188 & 0.3622 & 0.2314\end{pmatrix}\begin{matrix} HUE_1\\ VALUE_2\\ CHROMA_1\end{matrix}$$

Thus, $CT^{(2)}=(\underset{\rho\left(c,T_j^{(1)}\right)}{0.0017},\ \underset{\rho\left(c,T_j^{(2)}\right)}{0.1277},\ \underset{\rho\left(c,T_j^{(3)}\right)}{0.1107},\ \underset{\rho\left(c,T_j^{(4)}\right)}{0.2097},\ \underset{\rho\left(c,T_j^{(5)}\right)}{0.3110},\ \underset{\rho\left(c,T_j^{(6)}\right)}{0.1589},\ \underset{\rho\left(c,T_j^{(7)}\right)}{0.0803})$.

Evidently, $\vee_{k=1}^{7}\{\rho\left(c,T_j^{(k)}\right)\}=\rho\left(c,T_j^{(5)}\right)$, meaning that the color c is relevant to "*a little Wild*".

4.4.3 Validation of model

Three elements of color can form 27 types of colors to express different fashion themes (see Section 2.5.2). For each fashion theme, we invite the same panelists to give preferences or relevancies on each color expression. The evaluation scores are from the set of {-3, -2, -1, 0, 1, 2, 3}. The ultimate results are shown in Figure 4-21.



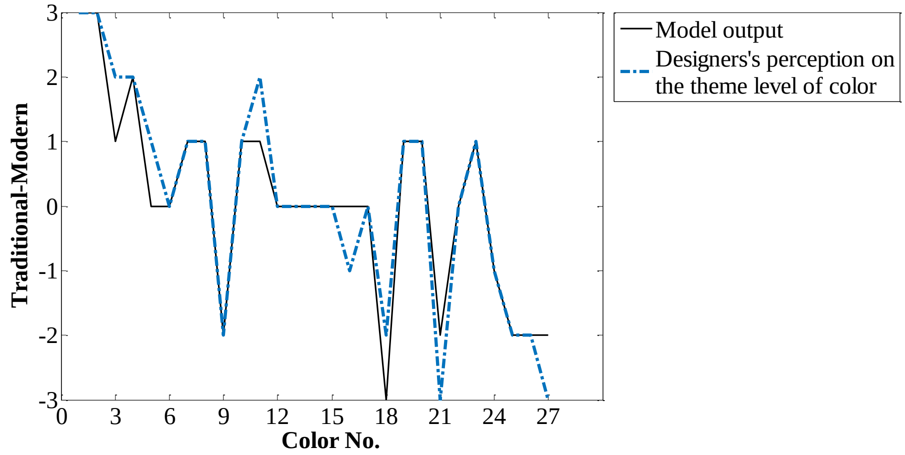


Figure 4-21 Comparison between the results of the model and the experts' perception on relevancy of colors to fashion themes

The values of Model_Error for each fashion theme are listed Table 4-6.

Table 4-6 The Model Error of each fashion theme related to colors

Fashion theme	T_1	T_2	T_3
Model Error	0.4714	0.4303	0.5092

From Table 4-6, we can find that the proposed model can be accepted since all the errors do not exceed 0.6 level of 7 (< 9%).

4.5 Modeling the Relationship between Fashion Themes and Fabrics (Model 5)

In this section, we set up the relation between fashion themes and fabrics by using rough sets. The flow diagram of Model 5 is shown in Figure 4-22 and the details of modeling are given in the following section.

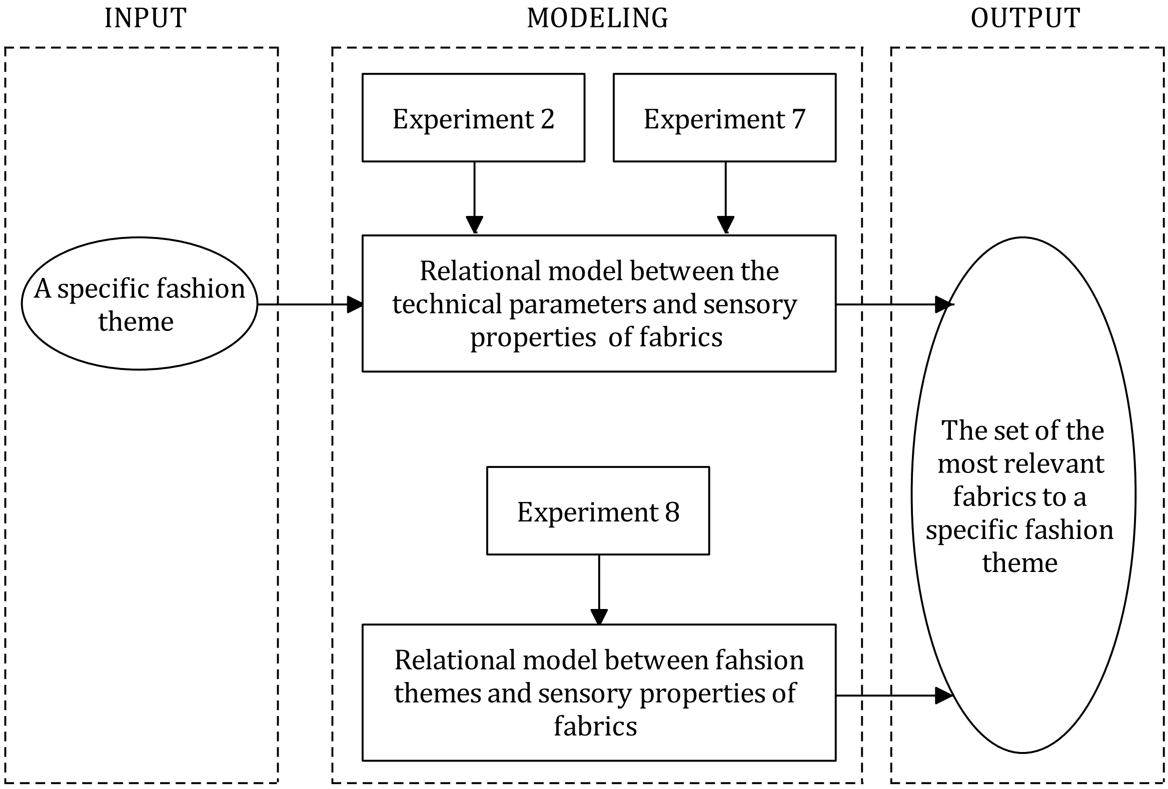


Figure 4-22 The functional Structure of Model 5

4.5.1 Modeling the relationship between technical parameters and sensory properties of fabrics

We set up a decision system for modeling the relationship between technical parameters and sensory properties of fabrics.

4.5.1.1 Fuzzification of technical parameters

From Experiment 2, we acquire the data of the u_1 (=11) fabric technical parameters tp_1~tp_{u_1}(See Section 2.2). According to the fuzzification method for body indices presented in Section 4.1.1, the technical parameter $tp_1$is a vector of different (from 1 to 5) fiber compositions and any other parameters of $tp_2, \ldots, tp_{u_1}$ is just a one-dimensional numerical value. In this situation, we use the fuzzy sets $\tilde{C}_k$'s ($k \in \{1, \ldots, 5\}$) to express each technical parameter by adopting the same definition as in Section 4.1.1, i.e. $\tilde{C}_k$="very small", … For tp_1, it can be represented by a vector of 5 fuzzy sets $\left(C(\tilde{C}_{i_1}),\ P(\tilde{C}_{i_2}),\ V(\tilde{C}_{i_3}),\ S(\tilde{C}_{i_4}),\ L(\tilde{C}_{i_5})\right)$, where C, P, V, S, L express the fiber compositions of Cotton, Polyester, Viscose, Spandex and Lyocell respectively with $i_1, \ldots, i_5 \in \{0,1,2, \ldots, 5\}$. $C(\tilde{C}_{i_1})$ means that the composition of cotton in this specific fabric corresponds to $\tilde{C}_{i_1}$ with $\tilde{C}_{i_1}$=$\tilde{C}_0$ $(i_1 = 0)$ if there is no cotton in the fabric. The other fuzzy sets $P(\tilde{C}_{i_2})$, $V(\tilde{C}_{i_3})$, $S(\tilde{C}_{i_4})$, $L(\tilde{C}_{i_5})$ can be explained in the same way.

Assume the fuzzy vector or fuzzy set corresponding to the value p_{ij} of the j-th technical parameter of fabric f_i (see Section 2.5.2) be $\bar{p}_{ij}$ with $i \in \{1,2,\dots,m\}$ and $j \in \{1,2,\dots,u_1\}$, where m is the total number of representative fabrics and u_1 the total number of the technical parameters of fabrics.

4.5.1.2 Identification of the sensory properties

From Experiment 7 in Section 2.4.3, we obtain the evaluation scores of each sensory property (all the five sensory properties include "soft-hard (sp_1)", "smooth-rough (sp_2)", "wrinkle resistance-crumply (sp_3)", "cool-warm (sp_4)" and "draping (sp_5)") of all the m fabrics in F (the set of the representative fabrics). The evaluation scores come from the set of seven linguistic levels of the sensory property, which can be expressed by seven fuzzy sets $\tilde{F}_1, \tilde{F}_2, \tilde{F}_3, \tilde{F}_4, \tilde{F}_5, \tilde{F}_6, \tilde{F}_7$ respectively (see Section 4.3.1). According to the method in Section 4.3.1, we obtain the fuzzy distribution $\tilde{F}_{ij}$ of the evaluation scores for all the evaluators on the i-th fabric (f_i) related to the j-th sensory property (sp_j) ($i \in \{1, 2, \dots, m\}, j \in \{1, 2, \dots, 5\}$).

Similar to the Equation (4-30), we compute the close degree $r(\tilde{F}_{ij}, \tilde{F}_k)$ of $\tilde{F}_{ij}$ to $\tilde{F}_k$ ($i \in \{1, \dots, m\}, j \in \{1, \dots, u_2\}, k \in \{1, \dots, 7\}$), where u_2 is the total number of the sensory properties of fabrics. The final evaluation score $\tilde{F}_{k^*}$ is computed from the maximum of the distribution of the close degrees for all the 7 levels, i.e. $r(\tilde{F}_{ij}, \tilde{F}_{k^*}) = \bigvee_{k=1}^{7} r(\tilde{F}_{ij}, \tilde{F}_k)$.

4.5.1.3 Relational model between the fabric technical parameters and sensory properties based on a decision system of rough sets

(1) The rules extraction in a complete decision system

If the data of all the fabric technical parameters $tp_1 \sim tp_{u_1}$ and the sensory property sp_l are known, we can set up a complete decision system as follows.

Table 4-7 A complete decision system on the relevancy of the technical parameters to a sensory property

Fabric	Condition attributes				Decision attribute
	tp_1	tp_2	$\cdots$	tp_{u_1}	sp_l
f_1	$\bar{p}_{11}$	$\bar{p}_{12}$	$\cdots$	$\bar{p}_{1u_1}$	e_{1l}
f_2	$\bar{p}_{21}$	$\bar{p}_{22}$	$\cdots$	$\bar{p}_{2u_1}$	e_{2l}
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
f_m	$\bar{p}_{m1}$	$\bar{p}_{m2}$	$\cdots$	$\bar{p}_{mu_1}$	e_{ml}

where $e_{il} \in \{\tilde{F}_1, \tilde{F}_2, \tilde{F}_3, \tilde{F}_4, \tilde{F}_5, \tilde{F}_6, \tilde{F}_7\}$ is the aggregated evaluation score of the i-th fabric on the sensory property sp_l given by all the evaluators.

From Table 4-9, we obtain a generalized decision rule as follows:

IF $tp_1 = \left(C(\tilde{C}_{i_1}), P(\tilde{C}_{i_2}), V(\tilde{C}_{i_3}), S(\tilde{C}_{i_4}), L(\tilde{C}_{i_5})\right)$ AND $\left(tp_2 = \tilde{C}_{j_2}\right)$ AND $\left(tp_3 = \tilde{C}_{j_3}\right)$ AND

... AND $\left(tp_{u_1} = \tilde{C}_{j_{u_1}}\right)$, **THEN** $sp_l = \tilde{F}_{k_l}$ (4-41)

where $l = 1, 2, \dots, u_2$ with $i_1, \dots, i_5 \in \{0,1,2, \dots ,5\}$, $j_2, \dots, j_{u_1} \in \{1,2, \dots ,5\}$, $k_l \in \{1,2, \dots, 7\}$.

Let R_{TP} (TP is the set of 5 technical parameters of fabrics) and $R_{\{sp_l\}}$ ($l \in \{1, \dots, u_2\}$) be two equivalence relations (see Section 3.2.3) on the universe F. According to R_{TP}, F is divided into p equivalence classes: $G_1, G_2, \dots, G_p$ (the corresponding values of each technical parameter are equal in each class). According to $R_{\{sp_l\}}$, F is divided into 7 equivalence classes: $D_1, D_2, \dots, D_7$ (the value of the sensory property sp_l is $\tilde{F}_{i_k}$ in each class D_k with $i_k \in \{1, \dots, 7\}, k = 1, \dots, 7$). Therefore, we obtain two equivalence divisions $F/R_{TP} = \{G_1, G_2, \dots, G_p\}$ and $F/R_{\{sp_l\}} = \{D_1, D_2, \dots, D_7\}$ on F.

Assume that the designer prefers to select one specific fabric meeting $sp_l = \tilde{F}_{i_{k^*}}$ ($k^* \in \{1, 2, \dots, 7\}$). If $\exists\, G_j \subseteq D_{k^*}$ or $\exists\, G_{j_1}, G_{j_2}, \dots, G_{j_q}$ ($j_1, \dots, j_q \in \{1, \dots, p\}$), s.t. $\bigcup_{x \in \{1,\dots,q\}} G_{j_x} \subseteq D_{k^*}$, D_{k^*} is a R-definable set. In this context, we can select one fabric from G_j or $\bigcup_{x \in \{1,\dots,q\}} G_{j_x}$ according to the Definition 3-8 of Chapter 3. Otherwise, D_{k^*} is a R-rough set and we need to compute the lower approximation $\underline{R}(D_{k^*})$ and upper approximation $\bar{R}(D_{k^*})$ of D_{k^*} (Definition 3-9 of Chapter 3). Since $\underline{R}(D_{k^*})$ is R-definable set and $\underline{R}(D_{k^*}) \subseteq D_{k^*}$ when $\underline{R}(D_{k^*}) \neq \emptyset$, we can select fabric from $\underline{R}(D_{k^*})$. The upper approximation $\bar{R}(D_{k^*})$ is not considered, because $D_{k^*} \subseteq \bar{R}(D_{k^*})$ and some fabrics in $\bar{R}(D_{k^*})$ but not belonging to in D_{k^*} cannot express the k^*-th evaluation level. We could make an incorrect decision once these elements (fabrics) in $\bar{R}(D_{k^*}) \setminus D_{k^*}$ are selected. Also, we have to select fabrics in $\bar{R}(D_{k^*})$ if $\underline{R}(D_{k^*}) = \emptyset$.

(2) The rules extraction in an incomplete decision system

If there are incomplete data in some technical parameters (unknown parameters), we set up an incomplete decision system (Table 4-8).

Table 4-8 An incomplete decision system on the theme levels of fabrics ("$*$" represents unknown parameters)

Fabric	Condition attribute					Decision attribute
	tp_2	tp_3	$\cdots$	tp_{u_1-1}	tp_{u_1}	sp_l
f_1	$\bar{p}_{12}$	$\bar{p}_{13}$	$\cdots$	$\bar{p}_{1,u_1-1}$	$*$	e_{1l}
f_2	$\bar{p}_{22}$	$*$	$\cdots$	$\bar{p}_{2,u_1-1}$	$\bar{p}_{2u_1}$	e_{2l}
f_3	$\bar{p}_{32}$	$*$	$\cdots$	$\bar{p}_{3,u_1-1}$	$*$	e_{3l}
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$	$\vdots$
f_{m-1}	$\bar{p}_{m-1,2}$	$\bar{p}_{m-1,3}$	$\cdots$	$*$	$\bar{p}_{m-1,u_1}$	$e_{m-1,l}$
f_m	$*$	$\bar{p}_{m3}$	$\cdots$	$\bar{p}_{m,u_1-1}$	$\bar{p}_{mu_1}$	e_{ml}

Let $TOL(TP)$ be a tolerance relation (see Section 3.2.4) on the universe F and $TOL_{TP}(x) = \{G_1, G_2, \ldots, G_p\}$ be the set of all the p tolerance classes $G_1, G_2, \ldots, G_p$ on F. Let $F/R_{\{sp_l\}} = \{D_1, D_2, \ldots, D_7\}$ be the equivalence division on F. We can exact the decision rules similar to the generalized form of (4-36) by using the tolerance relation. Some inconsistent decision rules have to be removed.

According to the designers' requirement, fabric can be selected from the lower approximation $\underline{TOL_{TP}}(D_k)$ of D_k if $\underline{TOL_{TP}}(D_k) \neq \emptyset$, and from the upper approximation $\overline{TOL_{TP}}(D_k)$ of D_k if $\underline{TOL_{TP}}(D_k) = \emptyset$ $(k \in \{1, \ldots, 7\})$.

4.5.2 Modeling the relationship between fashion themes and sensory properties of fabrics

According to Experiment 8, for each evaluator, we obtain a judgment (relevant or irrelevant) on the relation between each sensory property level and each fashion theme level. According to Section 2.4.3.6, for each sensory property and each fashion, their levels are all expressed by seven fuzzy sets $\tilde{F}_1, \tilde{F}_2, \tilde{F}_3, \tilde{F}_4, \tilde{F}_5, \tilde{F}_6, \tilde{F}_7$ (see Section 4.3.1).

We assume that $r_{kg}^{(lj)}$ represents the number of people among r panelists who consider that the k-th level of the sensory property sp_l $(k \in \{1, \ldots, 7\}, l \in \{1, \ldots, u_2\})$ is relevant to the g-th level of the fashion theme T_j $(j \in \{1, \ldots, t\})$. For example, if 3 evaluators consider that the sensory property "a little Soft" is relevant to "Rather Elegant" with $T_2 =$"Elegant" and $sp_1 =$ "Soft", then we have $r_{32}^{(12)} = 3$ with $k = 3$ and $g = 2$.

Denote $\mu_{kg}^{(lj)} = r_{kg}^{(lj)}/r$, and the relevancy of the k-th level $sp_l^{(k)}$ of the sensory property sp_l to the fashion theme T_j can be expressed by a fuzzy distribution on the set of $\{\tilde{F}_1, \tilde{F}_2, \tilde{F}_3, \tilde{F}_4, \tilde{F}_5, \tilde{F}_6, \tilde{F}_7\}$ as follows.

$$R\left(sp_l^{(k)}, T_j\right) = \left(\mu_{k1}^{(lj)},\ \mu_{k2}^{(lj)}, \ldots,\ \mu_{k7}^{(lj)}\right) \tag{4-42}$$

Thus, the relevancy of the sensory property sp_l to the fashion theme T_j can be expressed by a (7×7)-dimensional fuzzy relational matrix $FRM(sp_l, T_j)$ as follows.

$$FRM(sp_l, T_j) = \left(R\left(sp_l^{(1)}, T_j\right)^T,\ R\left(sp_l^{(2)}, T_j\right)^T,\ \ldots,\ R\left(sp_l^{(7)}, T_j\right)^T\right)^T$$

$$= \begin{pmatrix} \mu_{11}^{(lj)} & \mu_{12}^{(lj)} & \cdots & \mu_{17}^{(lj)} \\ \mu_{21}^{(lj)} & \mu_{22}^{(lj)} & \cdots & \mu_{27}^{(lj)} \\ \vdots & \vdots & \ddots & \vdots \\ \mu_{71}^{(lj)} & \mu_{72}^{(lj)} & \cdots & \mu_{77}^{(lj)} \end{pmatrix} \quad (l \in \{1, \ldots, u_2\}, j \in \{1, \ldots, t\}) \tag{4-43}$$

4.5.3 Modeling the relationship between fashion themes and technical parameters of fabrics

Assume the aggregated evaluation score (level) of a specific fabric f on the sensory property sp_l, provided by all the evaluators, is $\tilde{F}_{k_l}$ $(k_l \in \{1,2, \ldots, 7\}$ with $l = 1,2, \ldots, u_2)$.

We define M_j, i.e. the relevancy distribution of all the sensory properties related to the fashion theme T_j in the fabric f, as follows.

$$M_j = \frac{1}{u_2}\sum_{l=1}^{u_2} R\left(sp_l^{(k_l)}, T_j\right) = \left(\frac{1}{u_2}\sum_{l=1}^{u_2}\mu_{k_l 1}^{(lj)},\ \frac{1}{u_2}\sum_{l=1}^{u_2}\mu_{k_l 2}^{(lj)}, \ldots,\ \frac{1}{u_2}\sum_{l=1}^{u_2}\mu_{k_l 7}^{(lj)}\right)$$

$$\triangleq \left(m_1^{(j)},\ m_2^{(j)}, \ldots,\ m_7^{(j)}\right) \tag{4-44}$$

According the Fuzzy Selecting Near Principle (Section 3.1.5.2), for any fabric f, it corresponds to the g^*-th evaluation level of the fashion theme T_j if $m_{g^*}^{(j)} = \bigvee_{g=1}^{7}\{m_g^{(j)}\}$.

From this, we obtain the following decision rules.

$$\textbf{IF } \left(sp_1 = \tilde{F}_{k_1}\right) \text{AND} \cdots \text{AND } \left(sp_{u_2} = \tilde{F}_{k_{u_2}}\right), \textbf{THEN } T_j = \tilde{F}_{g^*} \text{ with } m_{g^*}^{(j)} = \bigvee_{g=1}^{7}\{m_g^{(j)}\} \tag{4-45}$$

Combining the two Rules (4-41) and (4-45), we obtain the decision rules on the relationship between the technical parameters of fabrics and the fashion theme T_j as follows.

$$\textbf{IF } tp_1 = \left(C(\tilde{C}_{i_1}), P(\tilde{C}_{i_2}), V(\tilde{C}_{i_3}), S(\tilde{C}_{i_4}), L(\tilde{C}_{i_5})\right) \text{ AND } \left(tp_2 = \tilde{C}_{j_2}\right) \text{ AND } \left(tp_3 = \tilde{C}_{j_3}\right) \text{AND}$$

$$\ldots \text{AND } \left(tp_{u_1} = \tilde{C}_{j_{u_1}}\right),\ \textbf{THEN } T_j = \tilde{F}_{g^*} \text{ with } m_{g^*}^{(j)} = \bigvee_{g=1}^{7}\{m_g^{(j)}\} \tag{4-46}$$

Using the above decision rules, we can classify all the fabric samples into the 7 evaluation levels of each fashion theme without making any ranking inside each evaluation level. For any given fashion requirement such as "Rather Elegant", we can always find all the fabrics corresponding to this level. In some cases, several fabrics can correspond to the same fashion theme level and the final choice will be done by the concerned designer according to his/her personal preference and other criteria.

4.5.4 An illustrative example

We give an example of fabrics recommendation related to the fashion theme T_2.

(1) Rules extraction of the relationship between technical parameters and sensory properties

According to Experiments 2 and 7, we set up an incomplete decision system. For obtaining more effective decision rules, we first reduce the number of attributes in this decision system by using the method of tolerance relation-based reduction in the incomplete decision system (Section 3.2.4.3). Generally, the results of attribute reduction are not unique in a decision system. However, as the data on the parameter tp_{11} (permeability) is not reliable due to the bad experimental condition, we finally select four sets of reduced attributes which does not include tp_{11} as follows:

$\{tp_1, tp_2, tp_3, tp_4, tp_5\}$, $\{tp_1, tp_3, tp_4, tp_5, tp_6\}$, $\{tp_1, tp_4, tp_5, tp_6, tp_7, tp_8, tp_9\}$ and $\{tp_1, tp_4, tp_5, tp_6, tp_7, tp_8, tp_{10}\}$.

The subset $\{tp_1, tp_4, tp_5\}$ has been repeated in all the above reduced set of attributes. Also, of all these 4 subsets of reduced attributes, $\{tp_1, tp_2, tp_3, tp_4, tp_5\}$ and $\{tp_1, tp_3, tp_4, tp_5, tp_6\}$ are more favorable because they both contain smaller numbers of attributes than the two other subsets. Considering the complexity and cost of fabric measurement, we select the reduction $\{tp_1, tp_2, tp_3, tp_4, tp_5\}$ since "Gram-Weight (tp_2)" is easier to be measured than "Warp Fracture-Strength (tp_6)" and the related cost is lower.

For the selected subset of attributes (fabric technical parameters), by using the general rule (4-41), we obtain the following 12 "**IF-THEN**" rules:

(r1) **IF** $tp_1 = \left(C(\tilde{C}_4), P(\tilde{C}_2), V(\tilde{C}_0), S(\tilde{C}_1), L(\tilde{C}_0)\right)$ AND $tp_2 = \tilde{C}_5$ AND $tp_3 = \tilde{C}_5$ AND $tp_4 = \tilde{C}_2$ AND $tp_5 = \tilde{C}_3$, **THEN** $sp_1 = \tilde{F}_5$ AND $sp_2 = \tilde{F}_6$ AND $sp_3 = \tilde{F}_3$ AND $sp_4 = \tilde{F}_5$ AND $sp_5 = \tilde{F}_6$

(r2) **IF** $tp_1 = \left(C(\tilde{C}_3), P(\tilde{C}_2), V(\tilde{C}_1), S(\tilde{C}_1), L(\tilde{C}_0)\right)$ AND $tp_2 = \tilde{C}_3$ AND $tp_3 = \tilde{C}_3$ AND $tp_4 = \tilde{C}_3$ *AND* $tp_5 = \tilde{C}_5$, *THEN* $sp_1 = \tilde{F}_4$ *AND* $sp_2 = \tilde{F}_4$ *AND* $sp_3 = \tilde{F}_4$ *AND* $sp_4 = \tilde{F}_6$ AND $sp_5 = \tilde{F}_3$

(r3) **IF** $tp_1 = \left(C(\tilde{C}_3), P(\tilde{C}_2), V(\tilde{C}_1), S(\tilde{C}_1), L(\tilde{C}_0)\right)$ AND $tp_2 = \tilde{C}_3$ AND $tp_3 = \tilde{C}_3$ AND $tp_4 = \tilde{C}_3$ AND $tp_5 = \tilde{C}_4$, **THEN** $sp_1 = \tilde{F}_6$ AND $sp_2 = \tilde{F}_5$ AND $sp_3 = \tilde{F}_6$ AND $sp_4 = \tilde{F}_5$ AND $sp_5 = \tilde{F}_5$

(r4) **IF** $tp_1 = \left(C(\tilde{C}_5), P(\tilde{C}_0), V(\tilde{C}_0), S(\tilde{C}_0), L(\tilde{C}_0)\right)$ AND $tp_2 = \tilde{C}_5$ AND $tp_3 = \tilde{C}_4$ AND $tp_4 = \tilde{C}_1$ AND $tp_5 = \tilde{C}_3$, **THEN** $sp_1 = \tilde{F}_7$ AND $sp_2 = \tilde{F}_7$ AND $sp_3 = \tilde{F}_2$ AND $sp_4 = \tilde{F}_3$ AND $sp_5 = \tilde{F}_7$

(r5) **IF** $tp_1 = \left(C(\tilde{C}_4), P(\tilde{C}_1), V(\tilde{C}_1), S(\tilde{C}_1), L(\tilde{C}_0)\right)$ AND $tp_2 = \tilde{C}_2$ AND $tp_3 = \tilde{C}_2$ AND $tp_4 = \tilde{C}_4$ AND $tp_5 = \tilde{C}_2$, **THEN** $sp_1 = \tilde{F}_5$ AND $sp_2 = \tilde{F}_3$ AND $sp_3 = \tilde{F}_7$ AND $sp_4 = \tilde{F}_1$ AND $sp_5 = \tilde{F}_2$

(r6) **IF** $tp_1 = \left(C(\tilde{C}_4), P(\tilde{C}_1), V(\tilde{C}_2), S(\tilde{C}_1), L(\tilde{C}_0)\right)$ AND $tp_2 = \tilde{C}_3$ AND $tp_3 = \tilde{C}_5$ AND $tp_4 = \tilde{C}_4$ AND $tp_5 = \tilde{C}_3$, **THEN** $sp_1 = \tilde{F}_2$ AND $sp_2 = \tilde{F}_5$ AND $sp_3 = \tilde{F}_7$ AND $sp_4 = \tilde{F}_7$ AND $sp_5 = \tilde{F}_2$

(r7) **IF** $tp_1 = \left(C(\tilde{C}_0), P(\tilde{C}_0), V(\tilde{C}_0), S(\tilde{C}_0), L(\tilde{C}_5)\right)$ AND $tp_2 = \tilde{C}_3$ AND $tp_3 = \tilde{C}_1$ AND $tp_4 = \tilde{C}_2$ AND $tp_5 = \tilde{C}_4$, **THEN** $sp_1 = \tilde{F}_1$ AND $sp_2 = \tilde{F}_1$ AND $sp_3 = \tilde{F}_5$ AND $sp_4 = \tilde{F}_1$ AND $sp_5 = \tilde{F}_1$

(r8) **IF** $tp_1 = \left(C(\tilde{C}_2), P(\tilde{C}_0), V(\tilde{C}_0), S(\tilde{C}_0), L(\tilde{C}_4)\right)$ AND $tp_2 = \tilde{C}_1$ AND $tp_3 = \tilde{C}_1$ AND $tp_4 = \tilde{C}_2$ AND $tp_5 = \tilde{C}_3$, **THEN** $sp_1 = \tilde{F}_1$ AND $sp_2 = \tilde{F}_3$ AND $sp_3 = \tilde{F}_5$ AND $sp_4 = \tilde{F}_2$ AND $sp_5 = \tilde{F}_2$

(r9) **IF** $tp_1 = \left(C(\tilde{C}_5), P(\tilde{C}_0), V(\tilde{C}_0), S(\tilde{C}_1), L(\tilde{C}_0)\right)$ AND $tp_2 = \tilde{C}_4$ AND $tp_3 = \tilde{C}_3$ AND $tp_4 = \tilde{C}_2$ AND $tp_5 = \tilde{C}_1$, **THEN** $sp_1 = \tilde{F}_5$ AND $sp_2 = \tilde{F}_6$ AND $sp_3 = \tilde{F}_4$ AND $sp_4 = \tilde{F}_4$ AND $sp_5 = \tilde{F}_5$

(r10) **IF** $tp_1 = \left(C(\tilde{C}_4), P(\tilde{C}_2), V(\tilde{C}_0), S(\tilde{C}_1), L(\tilde{C}_0)\right)$ AND $tp_2 = \tilde{C}_2$ AND $tp_3 = \tilde{C}_2$ AND $tp_4 = \tilde{C}_4$ AND $tp_5 = \tilde{C}_3$, **THEN** $sp_1 = \tilde{F}_6$ AND $sp_2 = \tilde{F}_5$ AND $sp_3 = \tilde{F}_6$ AND $sp_4 = \tilde{F}_2$ AND $sp_5 = \tilde{F}_6$

(r11) **IF** $tp_1 = \left(C(\tilde{C}_2), P(\tilde{C}_2), V(\tilde{C}_2), S(\tilde{C}_1), L(\tilde{C}_0)\right)$ AND $tp_2 = \tilde{C}_4$ AND $tp_3 = \tilde{C}_4$ AND $tp_4 = \tilde{C}_5$ AND $tp_5 = \tilde{C}_5$, **THEN** $sp_1 = \tilde{F}_3$ AND $sp_2 = \tilde{F}_3$ AND $sp_3 = \tilde{F}_3$ AND $sp_4 = \tilde{F}_7$ AND $sp_5 = \tilde{F}_5$

(r12) **IF** $tp_1 = \left(C(\tilde{C}_4), P(\tilde{C}_2), V(\tilde{C}_0), S(\tilde{C}_1), L(\tilde{C}_0)\right)$ AND $tp_2 = \tilde{C}_3$ AND $tp_3 = \tilde{C}_3$ AND $tp_4 = \tilde{C}_5$ AND $tp_5 = \tilde{C}_2$, **THEN** $sp_1 = \tilde{F}_3$ AND $sp_2 = \tilde{F}_2$ AND $sp_3 = \tilde{F}_3$ AND

$sp_4 = \tilde{F}_3$ AND $sp_5 = \tilde{F}_5$

In our experiment, the above rules correspond to 12 representative fabric samples of the set F, i.e. one fabric is characterized by one rule.

(2) Identification of the relation of each sensory property level and each fashion theme level

According to Experiment 8, we collect the responses of all the 15 evaluators for the theme T_2 and 5 sensory properties. The final results can be found in the following fuzzy relational matrices:

$$FRM(sp_1, T_2) = \overset{\displaystyle T_2}{\begin{array}{c} \begin{array}{ccccccc} \tilde{F}_1 & \tilde{F}_2 & \tilde{F}_3 & \tilde{F}_4 & \tilde{F}_5 & \tilde{F}_6 & \tilde{F}_7 \end{array} \\ \begin{pmatrix} 0 & 0.1 & 0.2 & 0.5 & 0.2 & 0 & 0 \\ 0 & 0.1 & 0.3 & 0.4 & 0.2 & 0 & 0 \\ 0 & 0.3 & 0.3 & 0 & 0.2 & 0.2 & 0 \\ 0.2 & 0.3 & 0.4 & 0.1 & 0 & 0 & 0 \\ 0.3 & 0.2 & 0.1 & 0.1 & 0.3 & 0 & 0 \\ 0 & 0.2 & 0 & 0.2 & 0.2 & 0.2 & 0.2 \\ 0 & 0.2 & 0.1 & 0.1 & 0.1 & 0.3 & 0.2 \end{pmatrix} \end{array}} \begin{array}{c} \text{extreme soft} \\ \text{soft} \\ \text{a little soft} \\ \text{neutral} \\ \text{a little hard} \\ \text{hard} \\ \text{extreme hard} \end{array} \quad sp_1$$

$$FRM(sp_2, T_2) = \overset{\displaystyle T_2}{\begin{array}{c} \begin{array}{ccccccc} \tilde{F}_1 & \tilde{F}_2 & \tilde{F}_3 & \tilde{F}_4 & \tilde{F}_5 & \tilde{F}_6 & \tilde{F}_7 \end{array} \\ \begin{pmatrix} 0.6 & 0.3 & 0.1 & 0 & 0 & 0 & 0 \\ 0.4 & 0.4 & 0.2 & 0 & 0 & 0 & 0 \\ 0.3 & 0.3 & 0.3 & 0.1 & 0 & 0 & 0 \\ 0.1 & 0.3 & 0.3 & 0.2 & 0.1 & 0 & 0 \\ 0 & 0 & 0.1 & 0.1 & 0.3 & 0.3 & 0.2 \\ 0 & 0 & 0 & 0 & 0.3 & 0.3 & 0.4 \\ 0 & 0 & 0 & 0 & 0.1 & 0.3 & 0.6 \end{pmatrix} \end{array}} \begin{array}{c} \text{extreme smooth} \\ \text{smooth} \\ \text{a little smooth} \\ \text{neutral} \\ \text{a little rough} \\ \text{rough} \\ \text{extreme rough} \end{array} \quad sp_2$$

$$FRM(sp_3, T_2) = \overset{\displaystyle T_2}{\begin{array}{c} \begin{array}{ccccccc} \tilde{F}_1 & \tilde{F}_2 & \tilde{F}_3 & \tilde{F}_4 & \tilde{F}_5 & \tilde{F}_6 & \tilde{F}_7 \end{array} \\ \begin{pmatrix} 0.6 & 0.3 & 0.1 & 0 & 0 & 0 & 0 \\ 0.3 & 0.3 & 0.3 & 0.1 & 0 & 0 & 0 \\ 0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0 & 0 \\ 0.1 & 0.3 & 0.3 & 0.2 & 0.1 & 0 & 0 \\ 0 & 0 & 0.1 & 0.1 & 0.3 & 0.3 & 0.2 \\ 0 & 0 & 0 & 0 & 0.2 & 0.3 & 0.5 \\ 0 & 0 & 0 & 0 & 0.1 & 0.2 & 0.7 \end{pmatrix} \end{array}} \begin{array}{c} \text{extreme wrinkle resistance} \\ \text{wrinkle resistance} \\ \text{a little wrinkle resistance} \\ \text{neutral} \\ \text{a little crumply} \\ \text{crumply} \\ \text{extreme crumply} \end{array} \quad sp_3$$

$$FRM(sp_4, T_2) = \overset{\displaystyle T_2}{\begin{array}{c} \begin{array}{ccccccc} \tilde{F}_1 & \tilde{F}_2 & \tilde{F}_3 & \tilde{F}_4 & \tilde{F}_5 & \tilde{F}_6 & \tilde{F}_7 \end{array} \\ \begin{pmatrix} 0 & 0.1 & 0.1 & 0.2 & 0.3 & 0.2 & 0.1 \\ 0 & 0 & 0 & 0.3 & 0.3 & 0.3 & 0.1 \\ 0 & 0.2 & 0.1 & 0.1 & 0.3 & 0.2 & 0.1 \\ 0 & 0.1 & 0.2 & 0.3 & 0.3 & 0.1 & 0 \\ 0.2 & 0.2 & 0.2 & 0.2 & 0.1 & 0.1 & 0 \\ 0.2 & 0.2 & 0.3 & 0.2 & 0.1 & 0 & 0 \\ 0.3 & 0.2 & 0.3 & 0.2 & 0 & 0 & 0 \end{pmatrix} \end{array}} \begin{array}{c} \text{extreme cool} \\ \text{cool} \\ \text{a little cool} \\ \text{neutral} \\ \text{a little warm} \\ \text{warm} \\ \text{extreme warm} \end{array} \quad sp_4$$

$$FRM(sp_5,T_2)=\begin{matrix} & \tilde{F}_1 & \tilde{F}_2 & \tilde{F}_3 & \overset{T_2}{\tilde{F}_4} & \tilde{F}_5 & \tilde{F}_6 & \tilde{F}_7 \\ \end{matrix} \begin{pmatrix} 0 & 0.1 & 0.2 & 0.6 & 0.1 & 0 & 0 \\ 0 & 0.1 & 0.2 & 0.5 & 0.2 & 0 & 0 \\ 0.4 & 0.3 & 0.3 & 0 & 0 & 0 & 0 \\ 0.3 & 0.3 & 0.3 & 0.1 & 0 & 0 & 0 \\ 0 & 0.1 & 0.2 & 0.3 & 0.2 & 0.2 & 0 \\ 0 & 0 & 0 & 0.2 & 0.3 & 0.3 & 0.2 \\ 0 & 0 & 0 & 0.1 & 0.2 & 0.3 & 0.4 \end{pmatrix} \begin{matrix} \text{extreme draped} \\ \text{draped} \\ \text{a little draped} \\ \text{neutral} \\ \text{a little non-draped} \\ \text{non-draped} \\ \text{extreme non-draped} \end{matrix} \; sp_5$$

From these results, we can obtain the most relevant level to each fabric for the specific fashion theme. Then, combining the rules (r1) ~ (r12) obtain the corresponding decision rules as follows.

(r1') **IF** $tp_1 = \left(C(\tilde{C}_4), P(\tilde{C}_2), V(\tilde{C}_0), S(\tilde{C}_1), L(\tilde{C}_0)\right)$ AND $tp_2 = \tilde{C}_5$ AND $tp_3 = \tilde{C}_5$ AND $tp_4 = \tilde{C}_2$ AND $tp_5 = \tilde{C}_3$, **THEN** $T_2 = \tilde{F}_5$ (A little Wild)

(r2') **IF** $tp_1 = \left(C(\tilde{C}_3), P(\tilde{C}_2), V(\tilde{C}_1), S(\tilde{C}_1), L(\tilde{C}_0)\right)$ AND $tp_2 = \tilde{C}_3$ AND $tp_3 = \tilde{C}_3$ AND $tp_4 = \tilde{C}_3$ AND $tp_5 = \tilde{C}_5$, **THEN** $T_2 = \tilde{F}_3$ (A little Elegant)

(r3') **IF** $tp_1 = \left(C(\tilde{C}_3), P(\tilde{C}_2), V(\tilde{C}_1), S(\tilde{C}_1), L(\tilde{C}_0)\right)$ AND $tp_2 = \tilde{C}_3$ AND $tp_3 = \tilde{C}_3$ AND $tp_4 = \tilde{C}_3$ AND $tp_5 = \tilde{C}_5$, **THEN** $T_2 = \tilde{F}_6$ (Rather Wild)

(r4') **IF** $tp_1 = \left(C(\tilde{C}_5), P(\tilde{C}_0), V(\tilde{C}_0), S(\tilde{C}_0), L(\tilde{C}_0)\right)$ AND $tp_2 = \tilde{C}_5$ AND $tp_3 = \tilde{C}_4$ AND $tp_4 = \tilde{C}_1$ AND $tp_5 = \tilde{C}_3$, **THEN** $T_2 = \tilde{F}_7$ (Extreme Wild)

(r5') **IF** $tp_1 = \left(C(\tilde{C}_4), P(\tilde{C}_1), V(\tilde{C}_1), S(\tilde{C}_1), L(\tilde{C}_0)\right)$ AND $tp_2 = \tilde{C}_2$ AND $tp_3 = \tilde{C}_2$ AND $tp_4 = \tilde{C}_4$ AND $tp_5 = \tilde{C}_2$, **THEN** $T_2 = \tilde{F}_4 \vee \tilde{F}_5$ (Neutral or a little Wild)

(r6') **IF** $tp_1 = \left(C(\tilde{C}_4), P(\tilde{C}_1), V(\tilde{C}_2), S(\tilde{C}_1), L(\tilde{C}_0)\right)$ AND $tp_2 = \tilde{C}_3$ AND $tp_3 = \tilde{C}_5$ AND $tp_4 = \tilde{C}_4$ AND $tp_5 = \tilde{C}_3$, **THEN** $T_2 = \tilde{F}_4$ (Neutral)

(r7') **IF** $tp_1 = \left(C(\tilde{C}_0), P(\tilde{C}_0), V(\tilde{C}_0), S(\tilde{C}_0), L(\tilde{C}_5)\right)$ AND $tp_2 = \tilde{C}_3$ AND $tp_3 = \tilde{C}_1$ AND $tp_4 = \tilde{C}_2$ AND $tp_5 = \tilde{C}_4$, **THEN** $T_2 = \tilde{F}_4$ (Neutral)

(r8') **IF** $tp_1 = \left(C(\tilde{C}_2), P(\tilde{C}_0), V(\tilde{C}_0), S(\tilde{C}_0), L(\tilde{C}_4)\right)$ AND $tp_2 = \tilde{C}_1$ AND $tp_3 = \tilde{C}_1$ AND $tp_4 = \tilde{C}_2$ AND $tp_5 = \tilde{C}_3$, **THEN** $T_2 = \tilde{F}_4$ (Neutral)

(r9') **IF** $tp_1 = \left(C(\tilde{C}_5), P(\tilde{C}_0), V(\tilde{C}_0), S(\tilde{C}_1), L(\tilde{C}_0)\right)$ AND $tp_2 = \tilde{C}_4$ AND $tp_3 = \tilde{C}_3$ AND $tp_4 = \tilde{C}_2$ AND $tp_5 = \tilde{C}_1$, **THEN** $T_2 = \tilde{F}_5$ (A little Wild)

(r10') **IF** $tp_1 = \left(C(\tilde{C}_4), P(\tilde{C}_2), V(\tilde{C}_0), S(\tilde{C}_1), L(\tilde{C}_0)\right)$ AND $tp_2 = \tilde{C}_2$ AND $tp_3 = \tilde{C}_2$ AND $tp_4 = \tilde{C}_4 \wedge tp_5 = \tilde{C}_3$, **THEN** $T_2 = \tilde{F}_6$ (Rather Wild) (r11') **IF** $tp_1 = \left(C(\tilde{C}_2), P(\tilde{C}_2), V(\tilde{C}_2), S(\tilde{C}_1), L(\tilde{C}_0)\right)$ AND $tp_2 = \tilde{C}_4$ AND $tp_3 = \tilde{C}_4$ AND $tp_4 = \tilde{C}_5$ AND $tp_5 = \tilde{C}_5$, **THEN** $T_2 = \tilde{F}_3$ (a little Elegant)

(r12') **IF** $tp_1 = \left(C(\tilde{C}_4), P(\tilde{C}_2), V(\tilde{C}_0), S(\tilde{C}_1), L(\tilde{C}_0)\right)$ AND $tp_2 = \tilde{C}_3$ AND $tp_3 = \tilde{C}_3$ AND $tp_4 = \tilde{C}_5\ AND\ tp_5 = \tilde{C}_2$, **THEN** $T_2 = \tilde{F}_2$ (Rather Elegant)

We can find that most of these 12 fabrics are relevant to the levels of "neutral" and "wild" for the fashion theme ""Elegant". This conclusion generally conforms to the nature of denim fabrics.

4.5.5 Validation of the model performance

For testing the performance of this model, we need to carry out a sensory experiment on the relevancy of fabrics to a specific fashion theme. The panelists in Group 1 (6 garment designers) and Group 3 (3 fabric designers) are invited to select the most relevant evaluation level of each fabric for a specific fashion theme, and the evaluation results are compared with the output results of the model (Figure 4-23). Here we only give the testing results for the fashion theme T_2 and others can be discussed similarly

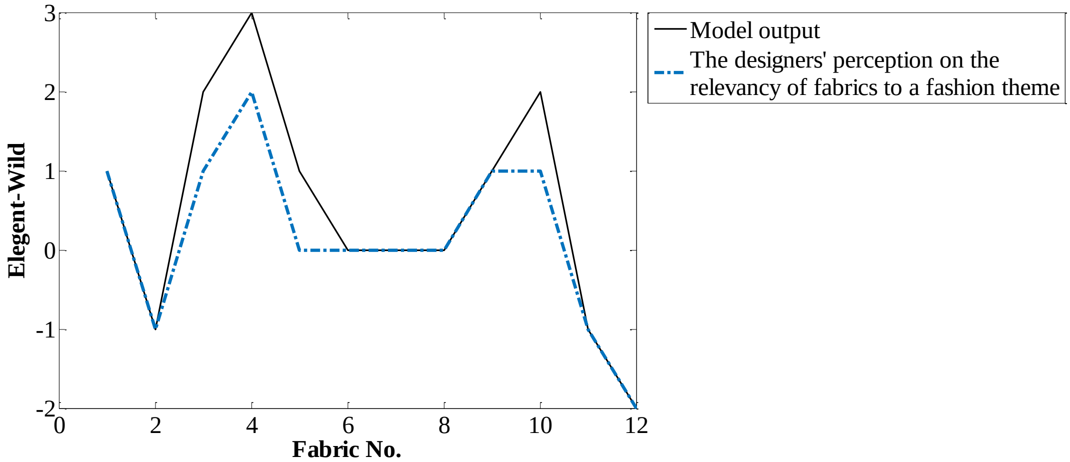


Figure 4-23 Comparison between the output results of the model and designers' perception on the relationship between fashion themes and fabrics

From Figure 4-22, we can find that the proposed model is efficient since all the values of Model_Error do not exceed 0.6 (0.5774) level of 7 (< 9%) in average. Therefore, the proposed model is acceptable.

4.6 Conclusion

In this chapter, we provide a systematic fashion theme-driven garment design process for a specific human body. In this design process, a number of mathematical models characterizing various relations have been set up by learning from data acquired in a series of physical and sensory experiments on human bodies, fabrics and fashion themes. The fuzzy techniques and rough sets have been used as key modeling tools.

We first classify measured human body dimensions into different body shape classes at six lower body positions by combining the linear regression analysis and fuzzy techniques (Section 4.1, Model 1). A person with a specific lower body shape in the target population can be represented by one body shape fuzzy vector, composed of the components on waist shape, abdomen shape, leg length, thigh shape and calf shape.

Based on the designers' knowledge on garment design acquired from the four sensory experiments, we set up four relational models between body shapes and basic design styles, and between a specific fashion theme and the main design factors (design styles, colors, fabrics) by using the fuzzy techniques (Models 2~4) and rough sets (Model 5). Different relevancy degrees characterizing the relation between body shapes and basic style elements, and that of style elements, color elements, fabric technical and sensory properties related to fashion themes, have been defined in this section. These proposed models clearly show the mapping relations between several sets, such as the set of body shapes, the set of design styles, the set of fashion themes, the set of colors and the set of fabrics. These relations are represented by a number of fuzzy relational matrices and fuzzy rules. The proposed models have been validated by comparing their output results with experts' evaluation.

Based on the above models, in Chapter 5, we will set up the design knowledge base and the final recommendation system, permitting to design a personalized garment for a specific human body.

CHAPTER 5 DESIGN KNOWLEDGE BASE AND DESIGNER - ORIENTED RECOMMENDATION SYSTEM

In this chapter, we first set up the design knowledge base for jeans using the ontologies, usually considered as powerful tools for modeling and formalizing various knowledge-based systems. Based on the relational models built in Chapter 4 and also represented by the ontologies, we propose a designer-oriented intelligent recommendation system with a feedback and self-adjusting function. Finally, two real cases are given for validating the proposed system.

5.1 General Introduction of knowledge base

Knowledge base (KB) is a technology to store complex structured and unstructured information used by a computer system [109]. Differing from database, a knowledge base can realize knowledge-based intelligent activities efficiently besides retrieving information. The ideal representation of a knowledge base is an object model with classes, subclasses, and instances.

A knowledge-based system (KBS) is a computer program to use a knowledge base to process the complex problems. It is an attempt to represent knowledge explicitly via tools such as ontologies and rules [110].

A knowledge base system generally includes knowledge source, user, software system, hardware system, and so on. The software system covers knowledge base (KB), inference engine (IG), knowledge base management system (KBMS), human-computer interaction (HCI), user interface (UI) and knowledge acquisition interface (KAI). Figure 5-1 shows the construction of a knowledge base system.

Knowledge base and inference engine constitute the core parts. Knowledge base is the foundation of the whole system. Inference engine is a control unit reasoning for the user's query according to the knowledge base.

Implementing of a knowledge base system covers three key techniques, including knowledge acquisition, knowledge representation and knowledge inference.

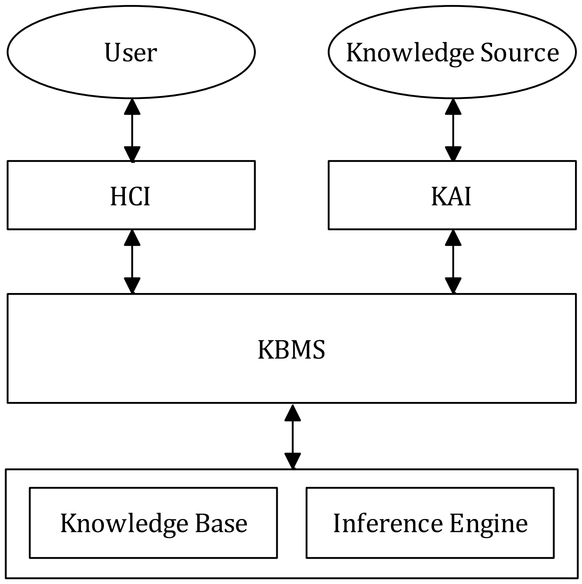


Figure 5-1 The construction of a knowledge base system

5.2 General notion of ontology

The term "ontology" derived from philosophy and studies the nature of being, becoming, existence or reality as well as the basic categories of being and their relations. Today, it also has practical applications in many other fields since it compartmentalizes the variables needed for some set of computations and establishes the relationships between them [111]. Some researchers in the field of artificial intelligence, drawing inspiration from philosophical ontologies, viewed computational ontology as a kind of applied philosophy [112-117].

Ontology represents knowledge according to the following four principles:

(1) Integration to knowledge;

(2) A good distinguishability;

(3) Combination of the variety and unity;

(4) A good extendibility.

5.2.1 Components of ontology

Ontologies share many structural similarities, regardless of the language in which they are expressed. Most of ontologies describe individual (instance), class (concept), attribute, and relation [118]. The general components of ontology in knowledge representation are below.

(1) Class (concept)

Class (concept) covers extensional and intensional definition. According to the extensional definition, they are abstract groups, sets, or collections of objects. According to the intensional definition, they are abstract objects that are defined by values of aspects that are constraints for being member of the class. Classes may classify individuals, other classes, or a combination of both. A class can subsume or be subsumed by other classes; a class subsumed by another is called a subclass (or subtype) of the subsuming class (or super type).

(2) Attribute

Objects in ontology can be described by relating them to other things, typically aspects, properties, features, characteristics, parts, or parameters that objects, which are called Attribute. Each attribute can be a class or an individual. For example, an object Garment has attributes:

<has as name> Garment

<has by definition as part > Style

(3) Relation

Relation between objects in ontology specifies how objects are related to other objects, and namely the ways in which classes and individuals can be related to one another.

An important type of relation is the subsumption relation ("is-a-superclass-of", "the converse of is-a", "is-a-subtype-of" or "is-a-subclass-of"). In such a structure, each object is the "child" of a "parent" class. Another common type of relations is the mereology relation, written as "part-of", which represents how objects combine to form composite objects.

The Relation types are sometimes domain-specific and are then used to store specific kinds of facts or to answer particular types of questions.

(4) Restriction

Restriction is formally stated descriptions of what must be true in order for some assertion to be accepted as input.

(5) Rule

Rules are the statements in the form of an if-then (antecedent-consequent) sentence that describes the logical inferences that can be drawn from an assertion in a particular form.

(6) Function term

Function terms are the complex structures formed from certain relations that can be used in place of an individual term in a statement.

(7) Axiom

Axioms are the assertions (including rules) in a logical form that together comprises the overall theory that the ontology describes in its domain of application.

(8) Individual

Individual (instance or object) is the basic or "ground level" components of ontology. The individuals in ontology may include concrete objects such as people and animals, as well as abstract individuals such as numbers and words.

(9) Event

Event is the changing of the attribute or relation.

5.2.2 Domain-ontology

The domain-ontology represents concepts which belong to part of the world. Particular meanings of terms applied to that domain are provided by domain ontology. For example, the word "pattern" has many different meanings. The ontology about the domain of fashion would model the "template" meaning. Ontology about the domain of mathematics would model the "mode" meaning. Mathematics is sometimes called the "Science of Pattern"[119], in the sense of rules that can be applied wherever needed. An ontology about the domain of architecture would model the "design" or "drawing" meanings [120].

5.3 Construction of Garment design Knowledge Base

At present, the majority of the ontology models in apparel field merely involve the classification knowledge of garment and the relations are only parent-child relationship between concepts, while relevant entities such as garment structure, garment design and complex relations are rarely concerned. In fact, it will be beneficial for recommendation of design schemes with existing knowledge if we can clarify the related concepts and relations in the process of garment design by using ontology. In Section 5.3.1, we will develop an ontology model for formalizing all the concepts and complex relations in the five models presented in Chapter 4. Then, in Section 5.3.2, we will set up the design knowledge base using this ontology model. This formalized knowledge base will be further used in Section 5.4 for building the design-oriented recommendation system and making inferences with this system for recommending the most relevant products.

5.3.1 Ontology model for garment design (Model 6)

Taking jeans design for women as sample, we acquire and build this ontology with expects' help, and set up the garment ontology model (GOM) by using a six-tuples as follows.

$$\text{GOM} = (\underset{\text{class}}{FD\_Class}, \underset{\text{relation}}{FD\_Relation}, \underset{\text{attribute}}{FD\_Attribute}, \underset{\text{rule}}{FD\_Rule}, \underset{\text{axiom}}{FD\_Axiom}, \underset{\text{instance}}{FD\_Instance})$$

Figure 5-2 shows the hierarchical structure of the ontology model.

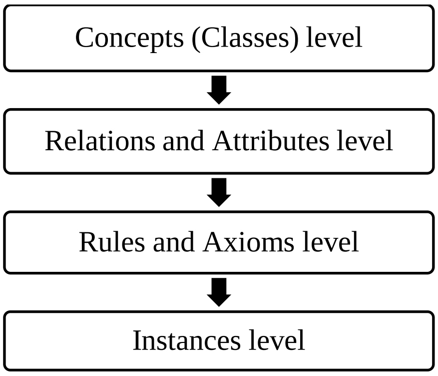


Figure 5-2 Hierarchical diagram of garment design ontology

Firstly, we define the related Classes according to experts' knowledge.

(1) Class (Concept)

FD_Class is composed of two parts as follows.

(a) Society entity

Society entity covers many aspects (e.g. human, circumstance, culture …), but here we just consider an entity – Human. It involves three classes (concepts) including Human, Young Women and Lower Body Shape.

(b) Product entity

In our research, Product entity covers garment categories such as Garments, Women's Garments, Women's Lower Garments, Women's Pants; components of garment structure such as Waistband, Front Panel, Back Panel; and various style elements related to garment design such as Fashion Themes, Design Styles, Fabric Properties, Colors, and so on. All of them are taken as the Classes (Concepts) of the garment design ontology.

On the basis of Concepts level, we build the Relations and Attributes level according to all the involved relations and attributes in our research.

(2) Relation

$$FD\_Relation = \{(c_1, c_2): c_1, c_2 \in FD\_Class\}$$

In my research, it involves some common relations such as "subclass of" and "part of" and some newly defined relations such as "fit-for", "carrier of" and "expression of". We use the following descriptive language to give the relations between classes.

Young Women is-a-subclass-of-Human

Women's Garment is-a-subclass-of Garment

Women's Lower Garment is-a-subclass-of Women's Garment

Women's Pants is-a-subclass-of Women's Lower Garment

Waistband is-by-definition-a-part-of-a Women's Pants

Front Panel is-by-definition-a-part-of-a Women's Pants

Back Panel is-by-definition-a-part-of-a Women's Pants

Style is-fit-for Lower Body Shape

Style is-a-expression-of Fashion Theme

Fabric is-a-expression-of Fashion Theme

Color is-a-expression-of Fashion Theme

In fact, there are more subclasses, such as 11 Technical Parameters and 5 Sensory Properties, in the class Fabric. In addition, new classes or new subclasses can be progressively introduced to the knowledge base with generation of new designs.

(3) Attribute

$$FD\_Arribute = \{(c_1, c_2): c_1, c_2 \in FD\_Class\}$$

We also use the following descriptive language to give attributes between classes.

(a) Human

<has as name> Human

<has by definition as part > Lower Body Shape

(b) Garment

<has as name> Garment

<has by definition as part > Fashion Theme

<has by definition as part > Design Style

<has by definition as part > Fabric Property

<has by definition as part > Color

(c) Style

<has as name> Style

<has by definition as part > Pattern

<has by definition as part > Waist Level

<has by definition as part > Leg-Opening Level

<has by definition as part > Detail

<has by definition as part > Accessory

(d) Fabric

<has as name> Fabric

<has by definition as part > Technical Parameter

<has by definition as part > Sensory Property

(e) Color

<has as name> Color

<has by definition as part > Hue

<has by definition as part > Value

<has by definition as part > Chroma

According to the relational models presented in Chapter 4 and design criteria, we build the Rules and Axioms level.

(4) Rule

$$FD\_Rule = \{S_1 \wedge \ldots \wedge S_n \wedge C \rightarrow S: S \in FD\_Class \cup FD\_Relation,$$
$$S_1, \ldots, S_n \in FD\_Class \cup FD\_Relation \cup FD\_Attribute, C \in FD\_Class\}$$

where C expresses a condition.

All of basic design rules in Chapter 4 are regarded as rules in design ontology. For example, the design rule of a jeans style is

$$\{p: p \in \text{Pattern}\} \wedge \{w: w \in \text{Waist Level}\} \wedge \{l: l \in \text{Leg Opening Level}\} \wedge \{d: d \in \text{Detail}\} \wedge \{a: a \in \text{Accessory}\} \wedge C \rightarrow \text{A Style}$$

Where C expresses a condition "just one pattern, one waist level and one leg opening level can be selected while multiple details and multiple accessories can be selected".

(5) Axiom

$$FD\_Axiom = \{S_1 \wedge \ldots \wedge S_n \rightarrow S: S \in FD\_Class \cup FD\_Relation,$$
$$S_1, \ldots, S_n \in FD\_Class \cup FD\_Relation \cup FD\_Attribute\}$$

FD_Axiom removes the condition C in FD_Rule, which shows whenever implications in FD_Axiom are true. There are the following axioms in the design ontology.

Axiom 1: Each class can be identified solely by a name.

Axiom 2: A subclass succeeds all relations of its parent class.

Axiom 3: A subclass succeeds all attributes of its parent class.

Since we focus on the jeans design in our research, we take the class Women's Jeans as an instance (individual) of the subclass Women's Pants of the class Women's Lower Garment.

(6) Instance (Individual)

$$FD\_Instance = \{S: S \in FD\_Class \cup FD\_Relation \cup FD\_Attribute\}$$

According to the above analysis, we can establish the tree structure diagram of the garment design ontology (Figure 5-3).

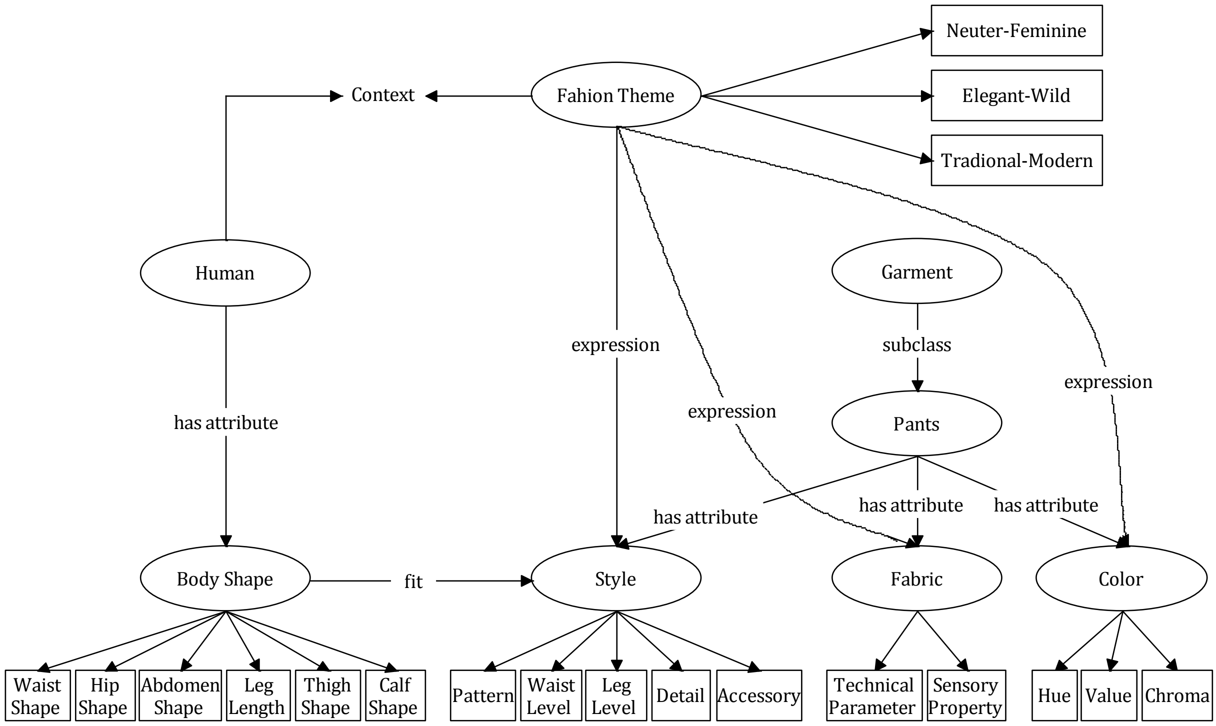


Figure 5-3 The tree structure diagram of garment design ontology

In fact, this ontology model could be extended by introducing new concepts, building more complex relations or adding new instances.

5.3.2 Ontology-based design knowledge base

The proposed design knowledge base has three layers as shown in Figure 5-4.

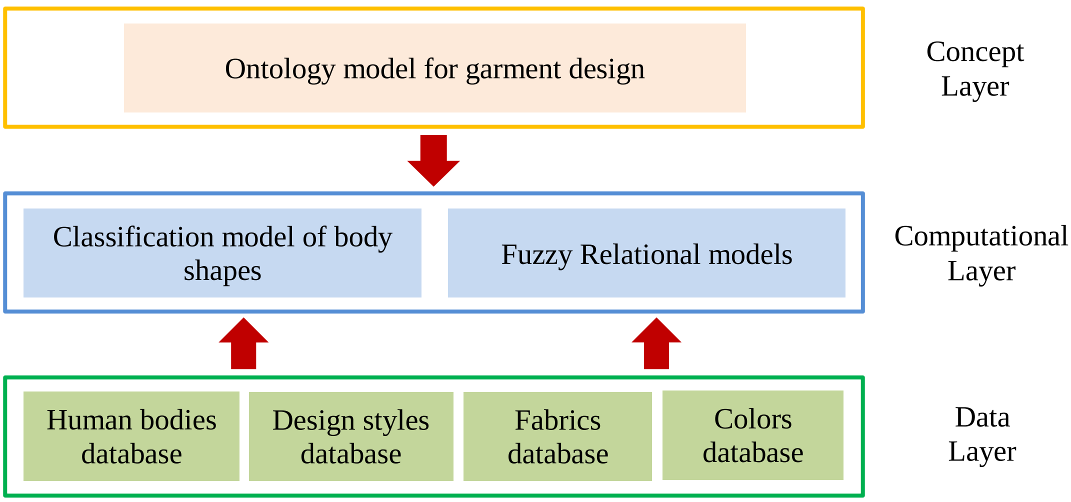


Figure 5-4 Hierarchical diagram of the design knowledge base

This knowledge base is organized following a hierarchical structure. All the raw data collected in the different databases (human bodies, styles, colors, fabrics) are stored in the data layer. The relevant concepts and the relations between various elements in the garment design are expressed by an ontology model for garment design in the concept layer in order to create a structured and complete knowledge base for further applications as a whole system. These data in data layer and the relations between concepts in the ontology model are analyzed quantitatively and modeled in the computational layer by using the five fuzzy models mentioned in Chapter 4 (classification of body shapes, relational models permitting to map body shapes, styles, colors and fabrics to fashion themes). It is the core of the knowledge base.

Also, the created knowledge base can be automatically adjusted at any time by introducing new knowledge into the knowledge base. Details will be further discussed in Section 5.4.3.

5.4 Designer-Oriented Recommendation System

Based on the structured design knowledge base proposed previously, the general scheme of the proposed design recommendation system is described in Figure 5-5.

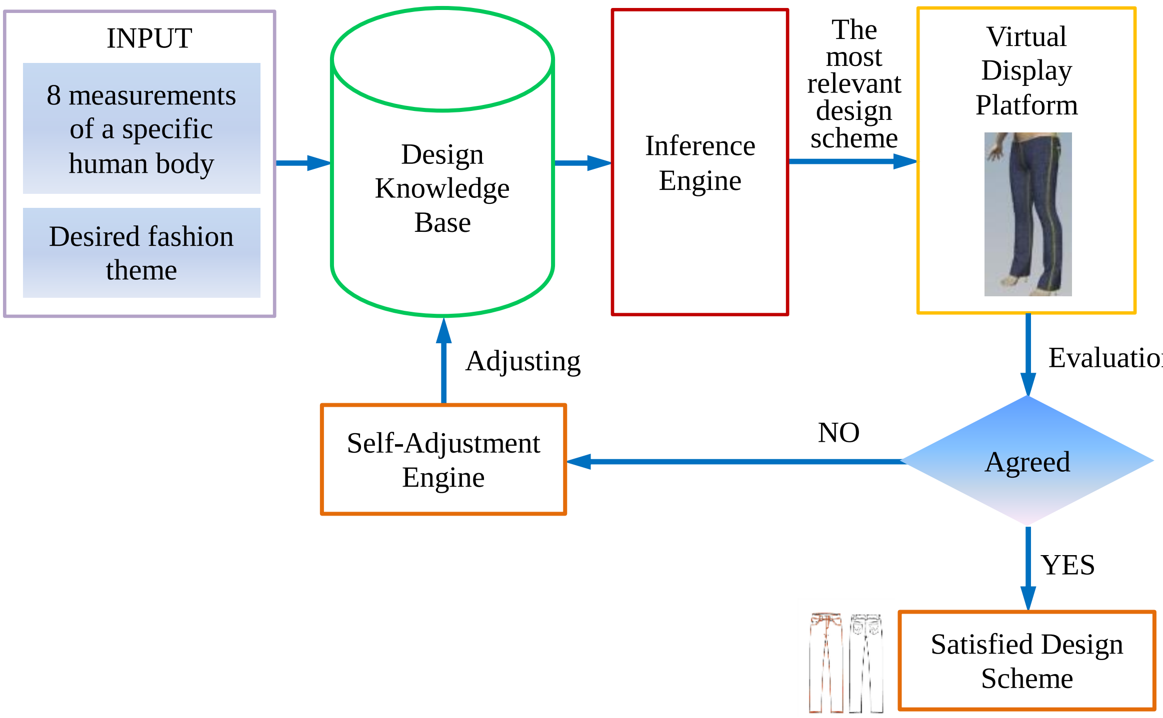


Figure 5-5 The proposed design recommendation system

In this system, Input is a user interface permitting the designer to input two categories of parameters, including a specific body shape represented by 8 key body dimensions and a specific desired fashion theme. The design knowledge acquired from designers is stored in Knowledge Base under the ontology form. Knowledge can be transformed into the design scheme by Inference Engine and then recommended to the user (designer). A recommended design scheme is displayed in a 3D virtual platform to the user who will determine, by using sensory evaluation, whether the design scheme conforms to the specific human body and the desired fashion theme or not. If the user is satisfied by the design scheme, she/he will validate it and then deliver it to the production unit for real garment prototyping. Otherwise, the designer needs to provide a feedback to system. Then, the system will adjust the knowledge base automatically by Self-Adjusting Engine and recommend a new design scheme again.

The proposed recommendation system permits to develop a new working cycle with feedback, i.e. *recommendation – 3D visualization – evaluation – adjustment*, which will be executed repeatedly until satisfaction of the designer in terms of consumer's body shape and desired fashion theme. The knowledge base can become more and more efficient by successively adding new design cases.

In the following section, we will introduce the principles of the functional blocks used in the recommendation system with more emphasis on the inference procedure from the structured knowledge base mentioned in Section 5.3 to recommendation of design schemes, the evaluation of recommended design schemes, and the self-adjusting of the knowledge base according to evaluation results.

5.4.1 The inference procedure for fashion recommendation

Denote the k^*-th evaluation level of the j-th fashion theme T_j as $T_j^{(k^*)}$ ($k^* \in \{1, 2, \dots, 7\}, j \in \{1, 2, \dots, t\}$, t is the total number of all the fashion themes). The purpose of this inference is to obtain the best design schemes related to $T_j^{(k^*)}$ for a specific human body.

In a general process of garment design, a fashion designer first selects a set of suitable styles according to the body shape of a specific consumer and the desired fashion theme. Then, this designer selects the fabrics the most relevant to the selected styles (not considering the color of fabrics) based on the desired fashion theme. Next, she/he identifies the most relevant colors on fabrics related to the desired fashion theme. In general, any desired color on fabrics can be realized in modern textile production conditions. The proposed inference procedure includes the following 6 steps:

Step 1: Identifying the body shape bs of a specific consumer according to Model 1 in Section 4.1.

Step 2: From the knowledge base, identifying the set of relevant basic styles related to the specific body shape bs, i.e. $S_1^R(bs) = \{s_1 \in S_1: f_{xyz} \geq Td\}$ (see Section 4.2).

Step 3: Expanding $S_1^R(bs)$ to the set of relevant styles $S_2(bs)$ ($\subset S$) (S is the set of all the styles) by adding detail and accessory elements. Finding the most relevant styles related to $T_j^{(k^*)}$ from $S_2(bs)$, i.e. $S^R\left(T_j^{(k^*)}\right) = \{s \in S_2(bs): \rho\left(s, T_j^{(k^*)}\right) = \vee_{k=1}^{7}\{\rho\left(s, T_j^{(k)}\right)\}\}$ (see Section 4.3.3). The styles which are the most relevant to $T_j^{(k^*)}$ are not unique.

Step 4: According to the rules (see Section 4.5.3) in the knowledge base, identifying the set of fabrics the most relevant to $T_j^{(k^*)}$, denoted as $F^R\left(T_j^{(k^*)}\right)$, of which each element corresponds to a numbered fabric in the fabrics base. The fabrics the most relevant to $T_j^{(k^*)}$ are not unique.

Step 5: Let C' be the set of colors of all the relevant fabrics in $F^R\left(T_j^{(k^*)}\right)$. From the knowledge base, identifying the set of the most relevant colors of C' to $T_j^{(k^*)}$, i.e. $C^R\left(T_j^{(k^*)}\right) = \{c \in C': \rho\left(c, T_j^{(k^*)}\right) = \vee_{k=1}^{7}\{\rho\left(c, T_j^{(k)}\right)\}\}$ (see Section 4.4.1).

Step 6: $DS = S^R\left(T_j^{(k)}\right) \times F^R\left(T_j^{(k)}\right) \times C^R\left(T_j^{(k)}\right) = \{(s, c, f): s \in S^R\left(T_j^{(k)}\right),\ f \in F^R\left(T_j^{(k)}\right),$ $c \in C^R\left(T_j^{(k)}\right)\}$ is regarded as the set of the relevant design schemes. The best design schemes will be selected from this set. In practice, there exist strong correlations between the sets of selected styles, fabrics and colors. Some combinations will enhance their relevancy degrees related to a specific level of the desired fashion theme. But some others cannot do that. For simplicity, we will neither aggregate these three sets to generate a unique relevancy degree nor make an overall ranking, but just show all the relevant design schemes of DS to the designer who will make his/her final decision according to the personal preference.

In some personalized design scenarios, the designer first selects the relevant fabrics and colors related to the desired fashion theme, then identifies the suitable styles according to the body shape of the specific consumer. In this context, the inference procedure is carried out according to the following steps: Step 4 – Step 5 – Step 1 – Step 2 – Step 3 – Step 6.

The inference procedure can be realized by the proposed garment ontology in Section 5.3.1. An example is shown in Figure 5-6.

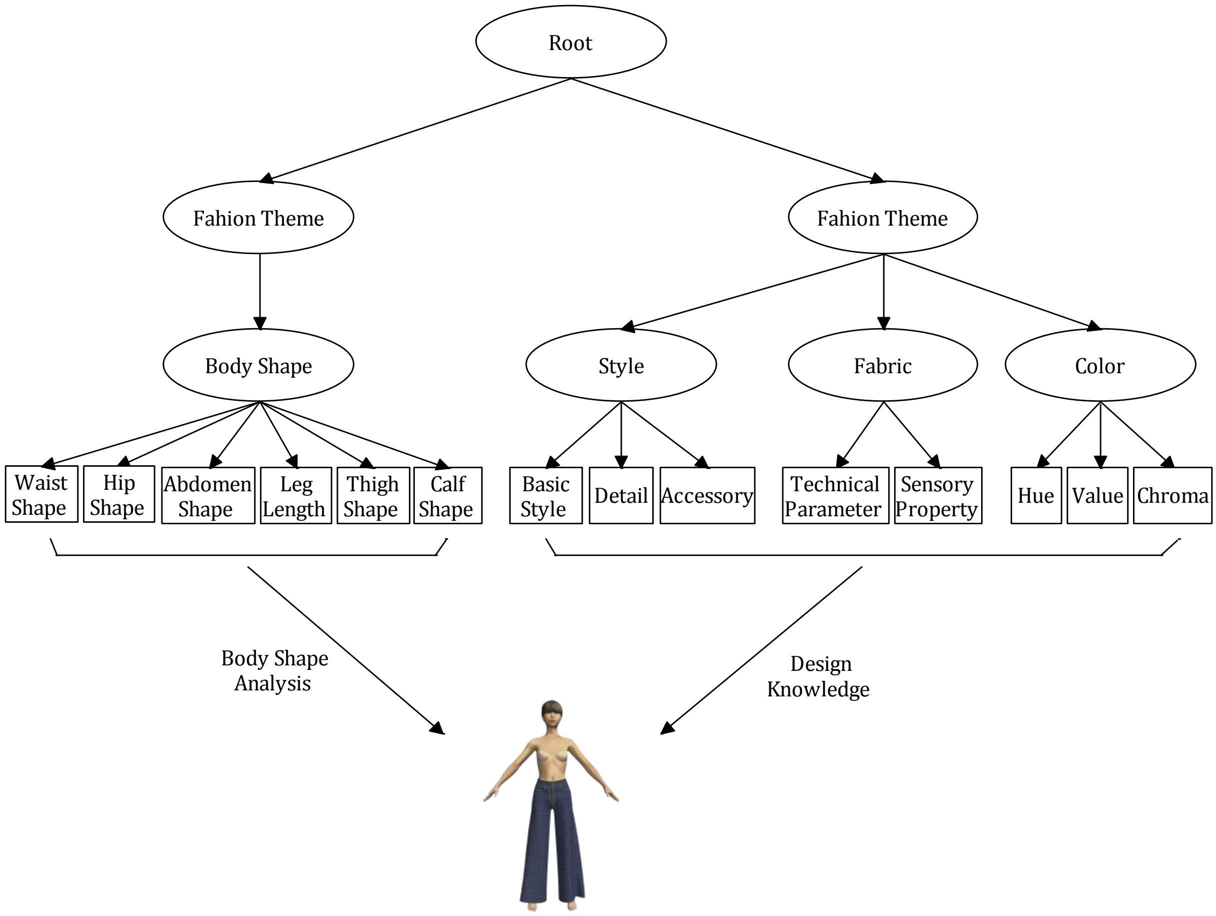


Figure 5-6 An example for ontology-based inference

All the children nodes of "Human" and "Fashion Theme" in the graph vary with the specific body shape and specific fashion theme. Ultimately, the inference engine enables to generate all the relevant design schemes, to be evaluated by the designer.

It is possible to use only one or several components the proposed system. During the recommendation procedure, we only activate the useful models of Model 2 ~ Model 5. For example, if we hope that the system recommends suitable fabrics only for a specific fashion theme, we just activate Model 5.

5.4.2 The virtual display and evaluation of the recommended results

In the proposed recommendation system, the final selection of a design scheme (fabric, color, style) will be realized by designer's evaluation on virtual fitting of the proposed relevant garment products on the consumer's body shape. The process is shown in Figure 5-7.

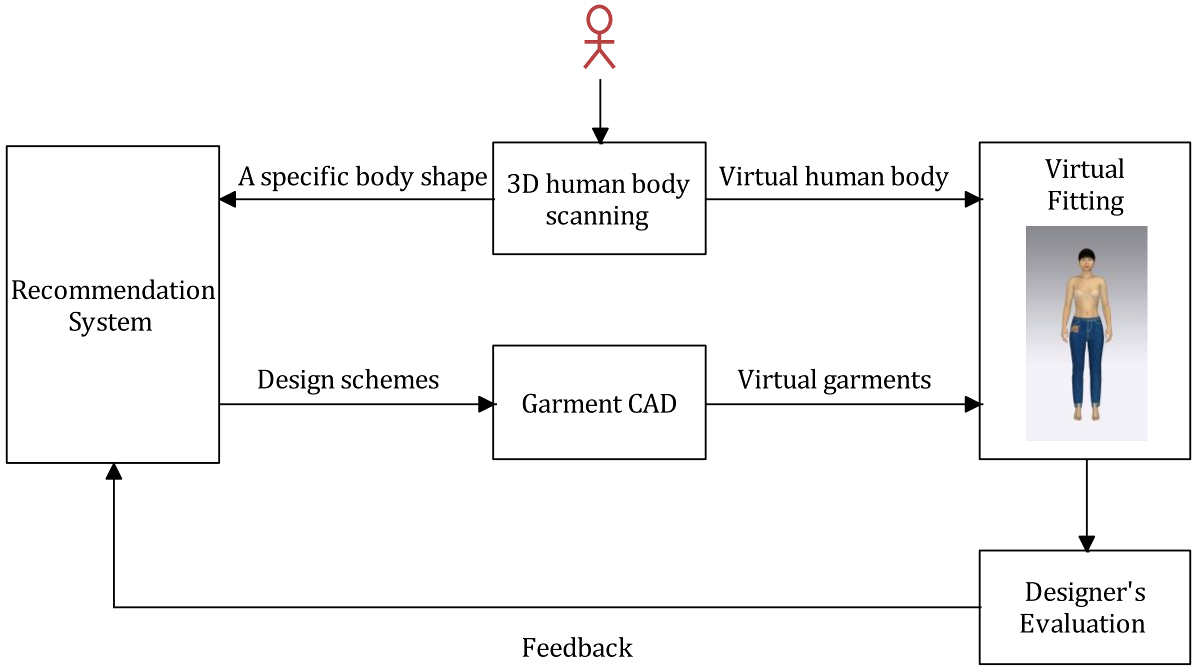


Figure 5-7 The flow chart of the evaluation and feedback

Before the evaluation of the virtual product, the designer spends about ten minutes on understanding of the purpose and method of evaluation. During the evaluation, the designer observes the 3D virtual product, generated by the garment CAD software according to the parameters of the recommended design scheme. This observation concerns the virtual fitting at static views from different angles (front, back, left, right, down, up, …) and dynamic display.

Although different designers may have different preferences on various design factors (style, fabrics, colors and level of fashion theme) of a product, the evaluation criteria of modular garment design are basically consistent for all the people. In our study, the designer will evaluate the recommended garment product in the two following aspects:

(1) Evaluation of the relevancy of the recommended design scheme related to garment fitting (not considering sizes)

The garment fitting is only related to the basic style in our model. The evaluation of garment fitting is realized using the three basic style components (Pattern, Waist-Level, Leg-Opening-Level). The evaluation values or levels (from low to high), corresponding to the style elements defined in Section 2.4.2, are shown on the fitting scale of Table 5-1.

Table 5-1 The evaluation values or levels corresponding to the style elements

Basic style component	Fitting level low level ←			→ high level
Pattern	Skinny	Slim	Straight	Loose
Waist-Level	Low-Waist	Regular-Waist		High-Waist
Leg-Opening-Level	Tapered Leg	Regular Leg	Boot-Cut	Wide-Bell

During the evaluation, the designer needs to indicate at which level the recommended design scheme is located for each basic style component. If the evaluation level is identical to the expected style element, then the corresponding basic style component can be accepted. Otherwise, an adjustment procedure will be performed. For example, if the designer considers that the recommended Pattern is "slim" (low level) and the expected style element on Pattern is "straight" (high level), then the system will make an adjustment.

(2) Evaluation of the relevancy of the recommended design scheme related to the desired fashion theme level

The evaluation procedure is similar to the previous one. For each fashion theme, the evaluation values of recommended design schemes correspond to the 7 levels defined in Figure 2-6 (Section 2.4.2). If the designer considers that the recommended design scheme corresponds to a fashion theme level different from his/her expected value, an adjustment procedure will be performed. Otherwise, the recommended design scheme will be accepted.

5.4.3 Feedback and Self-adjusting algorithms for the knowledge base

The proposed feedback mechanism permits to set up human-computer interactions so that the design knowledge base can be automatically adjusted according to the designer's evaluation results and a new design scheme is further recommended. The process can be executed repeatedly until the user's satisfaction. The knowledge base will be definitively modified if this adjustment is confirmed by a number of other designers. Otherwise, it is just a temporary modification of the knowledge base which has no impact on the other cases. According to the two evaluation aspects presented previously, we give the self-adjusting algorithm as follows.

(1) Self-adjusting algorithm related to the garment fitting deviation

In practice, we only need to adjust the relational matrix $R(BS, D_j)$ (see Section 4.2) since the relevancy of all the possible body shapes to each basic style is just determined by the corresponding relational matrix.

For simplicity, we only give the self-adjusting algorithm for one basic style component. Assume the evaluation values (levels) of the current recommended design scheme of Pattern, Waist-Level, Leg-Opening-Level be p_{i_0}, w_{j_0}, and l_{k_0} respectively for a specific human body, and the expected level of Pattern be p_{i_1} $(i_1 \neq i_0)$ and the levels of Waist-Level and Leg-Opening-Level be unchanged. According to the computation of the model (Model 2), the relevancy degree of the design style $(p_{i_0}, w_{j_0}, l_{k_0})$ related to the body shape is larger than the threshold Td. If we hope that the recommended result is moved to the level $p_{i_1}$of Pattern, then the relevancy degree of the design style $(p_{i_1}, w_{j_0}, l_{k_0})$ related to the body shape should be larger than Td. Meanwhile, the other elements in the concerned relational matrix should be changed at minimal level. In fact, for a specific body shape bs, we only need to adjust the specific relational matrix $R(bs, D_{i_1})$ (see Section 4.2). On this basis, we present the following self-adjusting algorithm on Pattern.

Step 1: For a specific body shape bs (the body shape matrix is $BODY$), computing the initial relational matrix and the relevancy degree of bs to each Pattern element (level) p_j $(j \in \{1, 2, 3, 4\})$.

According to Equation (4-22) in Section 4.2, we obtain an initial relational matrix:

$$R^0\left(bs, D_{i_1}\right) = BODY_{6\times\lambda} \circ R\left(BS, D_{i_1}\right)_{\lambda\times 3} = \left(r0_{uv}^{(j)}\right)_{6\times 3} \tag{5-1}$$

According to Equation (4-27) in Section 4.2, we obtain the initial close degree r_j^0 of the level p_j of Pattern $(j \in \{1, 2, 3, 4\})$ related to bs.

Step 2: Setting up the adjustment model for the relational matrix $R\left(bs, D_{i_1}\right)$.

A new relational matrix $R^1\left(bs, D_{i_1}\right) = \left(r_{uv}^{(j)}\right)_{6\times 3}$ can be computed by the following nonlinear model.

$$\begin{aligned} \min \quad & \left\| R^1\left(bs, D_{i_1}\right) - R^0\left(bs, D_{i_1}\right) \right\| \\ \text{s.t.} \quad & f_{i_1 j_0 k_0} \geq Td \end{aligned} \tag{5-2}$$

where $f_{i_1 j_0 k_0}$ is the relevancy degree of the design style $(PATTERN_{i_1},\ WAIST_{j_0},\ LEG_{k_0})$ to bs.

Since it is difficult to obtain the exact solution of the nonlinear model, we try to find an approximate solution by using a Genetic Algorithm (GA) under an appropriate number of iterations.

(a) Let the maximal number of iterations in the GA be Th. We randomly generate n (6×3)-dimensional matrices on the interval $(0, 1)$, taken as the initial population $P(0)$ of $R\left(bs, D_j\right)$.

(b) Let t be the current iteration no. of the GA, we compute the fitness of every individual in the population $P(t)$.

The fitness function is defined by

$$\text{fitness} = 1 \Bigg/ \left[\sum_{u=1}^{6}\sum_{v=1}^{3}\left(r_{uv}^{(j)} - r0_{uv}^{(j)}\right)^2 + \lambda\left(f_{i_1 j_0 k_0} - Td\right)^2\right] \tag{5-3}$$

where λ is a penalty coefficient.

(c) According the fitness function, the next population $P(t+1)$ is generated after executing selection, crossover and mutation.

(d) Repeating the above operations until satisfying the terminating condition: the relational matrix $R^t\left(bs, D_j\right)$ is unchanged or $t = Th$ (the maximal number of iterations has been reached).

(e) Obtaining an approximate solution $R^t\left(bs, D_{i_1}\right)$.

Step 3: Updating the knowledge base.

The new relational matrix $R^t\left(BS, D_{i_1}\right)$ (integration of the change of $R^t\left(bs, D_{i_1}\right)$ for one single body shape bs into the overall matrix $R\left(BS, D_{i_1}\right)$) is taken as a temporary knowledge on the relationship between body shapes and Pattern and will be used in the current recommendation. It has no impacts on the other recommendation cases. The permanent knowledge base, i.e. the former matrix $R\left(BS, D_{i_1}\right)$, will be definitively modified only when several designers confirm the change of $R^t\left(bs, D_{i_1}\right)$ in different cases.

Step 4: According to the new knowledge base $R^t\left(BS, D_{i_1}\right)$, the system recommends a new design style.

Step 5: The self-adjustment algorithm stops until designer's satisfaction. Otherwise, the algorithm returns to Step 2 for repeating the procedure again.

(2) Self-adjusting algorithm related to the expected level of fashion theme

Taking fabric recommendation as example, we present the self-adjusting algorithm on processing of deviation of the fashion theme level of the recommended design scheme related to the designer's expectation. In this algorithm, the concerned symbols have been defined in Sections 4.5.2 and 4.5.3.

For a given level of the fashion theme T_j, the recommendation system can generate a relevant fabric according to Model 5. However, the current fashion theme level of the recommended fabric, identified by a set of sensory properties sp_l $(l = 1, 2, \ldots, u_2)$, may not conform to the designer's expectation. In this case, it is necessary to adjust the established knowledge base, i.e. all the corresponding relational matrices $FRM(sp_l, T_j)$ $(l = 1, 2, \ldots, u_2)$.

For a specific fashion theme T_j $(j = 1, 2, \ldots, t)$, we assume that the fashion theme level of the recommended fabric, calculated from Model 5, is i_0 $(1 \le i_0 \le 7)$ and the expected fashion theme level is i_1 $(1 \le i_1 \le 7)$. The aim of the adjustment is to generate a new fabric corresponding to i_1 level of the fashion theme T_j. In this case, the relevancy degree related to the i_1 level of T_j is larger than those at the other levels. Meanwhile, we hope that the distribution of the relevancy degrees of the recommended fabric related to all the levels of T_j is changed at minimal level. On this basis, we propose the self-adjusting algorithm on fabric recommendation as follows.

Step 1: For the fashion theme T_j $(j \in \{1, \ldots, t\})$, we have u_2 initial relational matrices $FRM^0(sp_l, T_j) = \left(\mu 0_{pq}^{(lj)}\right)_{7\times 7}$ $(l = 1, \ldots, u_2)$ from the knowledge base. These matrices permit to generate u_2 initial fuzzy distributions (the k_l-th $(l = 1, \ldots, u_2)$ row of $FRM^0(sp_l, T_j)$):

$$R^0\left(sp_l^{(k_l)}, T_j\right) = \left(\mu 0_{k_l 1}^{(lj)}, \mu 0_{k_l 2}^{(lj)}, \ldots, \mu 0_{k_l 7}^{(lj)}\right) \qquad (l = 1, 2, \ldots, u_2)$$

Step 2: Setting up the adjustment model of the u_2 fuzzy relational matrices $FRM(sp_l, T_j)$.

In practice, we only need to adjust the elements in the k_l-th $(l = 1, \ldots, u_2)$ row of each $FRM(sp_l, T_j)$, i.e. $R\left(sp_l^{(k_l)}, T_j\right)$, while the other elements are unchanged.

We denote the adjusted fuzzy distribution by

$$R^1\left(sp_l^{(k_l)}, T_j\right) = \left(\mu_{k_l 1}^{(lj)}, \mu_{k_l 2}^{(lj)}, \ldots, \mu_{k_l 7}^{(lj)}\right)$$

They can be identified by the following nonlinear model.

$$\min \sum_{l=1}^{u_2} \left\| R^1\left(sp_l^{(k_l)}, T_j\right) - R^0\left(sp_l^{(k_l)}, T_j\right) \right\|$$

$$\text{s.t.} \quad \sum_{l=1}^{u_2} \mu_{k_l i_1}^{(lj)} \ge \sum_{l=1}^{u_2} \mu_{k_l q}^{(lj)} \qquad (q = 1, \ldots, 7; q \ne i_1) \tag{5-4}$$

Since it is difficult to obtain the exact solution of the nonlinear model, we also try to find an approximate solution using a GA under an appropriate number of iterations.

(a) Let the maximum number of iterations be Th. For any $k \in \{1,2,\ldots,u_2\}$, we randomly generate nu_2 7-dimensional vectors in the interval $(0,1)$, taken as the initial population $P(0)$ of $R\left(sp_l^{(k_l)},T_j\right)$.

(b) Let t be the iteration number, of the GA, we compute the fitness function of each individual in the population $P(t)$.

We define the fitness function as follows.

$$\text{fitness} = 1\Bigg/\left[\sum_{l=1}^{u_2}\sum_{q=1}^{7}\left(\mu_{k_lq}^{(lj)} - \mu0_{k_lq}^{(lj)}\right)^2 + \sum_{q=1}^{7}\lambda_q\left(\sum_{l=1}^{u_2}\left(\mu_{k_lq}^{(lj)} - \mu_{k_li_1}^{(lj)}\right)\right)^2\right] \tag{5-5}$$

(c) According to this fitness function, the next population $P(t+1)$ is generated after the operations of selection, crossover and mutation.

(d) The above operations are executed repeatedly until satisfying the terminating condition: $R^t\left(sp_l^{(k_l)},T_j\right)$ is unchanged or $t = Th$ (the maximal number of iterations has been reached).

(e) Finally, we obtain the approximate solutions $R^t\left(sp_l^{(k_l)},T_j\right)$ $(l = 1,\ldots,u_2)$.

Step 3: Updating the knowledge base.

The new relational matrix $FRM^t(sp_l,T_j)$ (integration of the change of $R^t\left(sp_l^{(k_l)},T_j\right)$ for one level of one sensory property of fabric into the overall matrix $FRM(sp_l,T_j)$) is taken as a temporary knowledge on the relationship between the sensory property sp_l of fabric and the fashion theme T_j and will be used in the current recommendation. It has no impacts on the other recommendation cases. The permanent knowledge base, i.e. the former matrix $FRM(sp_l,T_j)$, will be definitively modified only when several designers confirm the change of $R^t\left(sp_l^{(k_l)},T_j\right)$ in different cases.

Step 4: According to new knowledge base $FRM^t(sp_l,T_j)$, the system recommends a new fabric again.

Step 5: The self-adjustment algorithm stops until designer's satisfaction. Otherwise, the algorithm returns to Step 2 for repeating the procedure again.

If several fashion themes are considered simultaneously by the fashion designer, the system will recommend a list of relevant design schemes (styles, fabrics, colors) for each of them. Then, an intersection operation will be carried out for all the lists computed from all the fashion themes in order to obtain the final list of design schemes.

5.4.4 Application cases in garment design

5.4.4.1 Validation of new fashion products (Case 1)

The aim of this case is to validate 1) whether the proposed new fashion products are conform or not to the specific body shape and the desired fashion theme; 2) whether the three design factors (style, fabric and color) are conform each other in each new fashion product. The positive responses to these two questions enable to validate the proposed new garment products. The virtual fitting effects of these products on the selected body shapes are provided at the end of this section.

The basic input data of Case 1 is given below.

(a) Target population

Two specific human bodies (body_1 and body_2 mentioned in Section 4.1) are selected from the target population (young women of 18-25 years in Central China).

(b) Fashion theme

"Neuter-Feminine (T_1)" is taken as fashion theme for designing personalized jeans.

(c) New fashion products

We consider the design schemes of two new fashion products as follows.

Product_1 = <style_1, fabric_1, color_1>, Product_2 = <style_2, fabric_2, color_2>.

where style_1 =

$(\underset{PATTERN_3}{Straight},\ \underset{WAIST_3}{High\text{-}Waist},\ \underset{LEG_1}{Tapered\text{-}Leg},\ \underset{DETAIL_{11}}{Crescent\ Front\text{-}Pocket},\ \underset{DETAIL_{21}}{Uncovered\ Back\text{-}Pocket},$

$\underset{DETAIL_{31}}{Fasteners\ Front\text{-}Fly},\ \underset{DETAIL_{41}}{Hidden\ Side\text{-}Seam},\ \underset{DETAIL_{51}}{no\text{-}Patchwork},\ \underset{DETAIL_{61}}{no\text{-}Holey},\ \underset{ACCESSORY_2}{Embroidery})$

basic style_1 = $(\underset{PATTERN_3}{Straight},\ \underset{WAIST_3}{High\text{-}Waist},\ \underset{LEG_1}{Tapered})$ (see Table 2-5)

fabric_1 =

$(tp_1$(C: 47.3%, P: 31.7%,V: 18.0%, S: 3.0%, L: 0%)$, tp_2(323), tp_3(0.57), tp_4(430), tp_5(304))$

color_1 = $(\underset{HUE_1}{low\text{-}Hue},\ \underset{VALUE_2}{middle\text{-}Value},\ \underset{CHROMA_3}{high\text{-}Chroma})$ (see Section 4.4.1)

style_2 =

$(\underset{PATTERN_1}{Skinny},\ \underset{WAIST_2}{Regular\text{-}Waist},\ \underset{LEG_3}{Boot\text{-}Cut},\ \underset{DETAIL_{11}}{Crescent\ Front\text{-}Pocket},\ \underset{DETAIL_{21}}{Uncovered\ Back\text{-}Pocket},$

$\underset{DETAIL_{31}}{Fasteners\ Front\text{-}Fly},\ \underset{DETAIL_{41}}{Hidden\ Side\text{-}Seam},\ \underset{DETAIL_{51}}{no\text{-}Patchwork},\ \underset{DETAIL_{61}}{no\text{-}Holey},\ \underset{ACCESSORY_1}{Lace},\ \underset{ACCESSORY_5}{Diamonds})$

basic style_2 = $(\underset{PATTERN_1}{Skinny},\ \underset{WAIST_2}{Regular\text{-}Waist},\ \underset{LEG_3}{Boot\text{-}Cut})$

fabric_2 =

$(tp_1$(C: 35.7%, P: 0%,V: 0%, S: 0%, L: 64.3%)$, tp_2(182), tp_3(0.39), tp_4(400), tp_5(205.4))$

color_2 $= (\underset{HUE_1}{low\text{-}Hue},\ \underset{VALUE_1}{low\text{-}Value},\ \underset{CHROMA_3}{high\text{-}Chroma})$

The expected fashion theme level of Product_1 is “a little Feminine” and that of Product_2 is “a little Neuter”.

From these input data, the recommendation system will first test if the new products or design schemes are conform to the specific body shapes.

According to our strategy, only the design of basic styles is related to the body shapes. Therefore, we just need to consider whether the basic style of a new product is relevant or not to the specific body shapes. This relevancy degree corresponds to the output of Model 2 (Section 4.2).

From the computation of Model 1 (Section 4.1), we obtain the body shape vectors of the two body shapes, taken as input of Model 2. And then, the system computes the relevancy degrees between the basic styles of these two new design schemes and the two specific body shapes respectively (Model 2). The predefined threshold value in Model 2 is set to 0.9 and the users can adjust it in the interval $(0, 1)$ freely.

Table 5-1 The relevancy degrees of the basic style_1 to the two body shapes

Body shape	relevancy degree	fit
body_1	0.7665	NO
body_2	0.9670	YES

Table 5-2 The relevancy degrees of the basic style_2 to the two body shapes

Body shape	relevancy degree	fit
body_1	0.9011	YES
body_2	−0.0157	NO

From the above results, we can find that the first design scheme is relevant to body_2 but irrelevant to body_1, and the second one fits for body_1 but unfits for body_2. However, the first design scheme cannot be completely rejected for body_1 because its relevancy degree is not far from the threshold. It can be further improved by making some changes in the design factors. The second design scheme is completely rejected for body_2 since the corresponding relevancy degree is negative.

Next, we will test if the new products or design schemes are conform to the selected fashion theme.

This validation will be performed by the outputs of Model 3 ~ Model 5 (Section 4-3 ~ 4-5). These models permit to identify the level of fashion theme T_1 for each of the three design factors. The final results are listed in Table 5-3.

Table 5-3 The "Neuter-Feminine" levels of the three design factors

New product	Style	Fabric	Color	Conformity
Product_1	$\tilde{F}_5$	$\tilde{F}_5$	$\tilde{F}_5$	YES
Product_2	$\tilde{F}_3$	$\tilde{F}_3$	$\tilde{F}_3$	YES

For the fashion theme T_1, it can be seen that, for each new product, the fashion theme levels corresponding to all the three design factors are conform each other (all "$\tilde{F}_5$ (a little Feminine)" for Prodct_1 and all "$\tilde{F}_3$ (a little Neuter)" for Product_2). It shows that these two new products can successfully express the expected fashion theme levels.

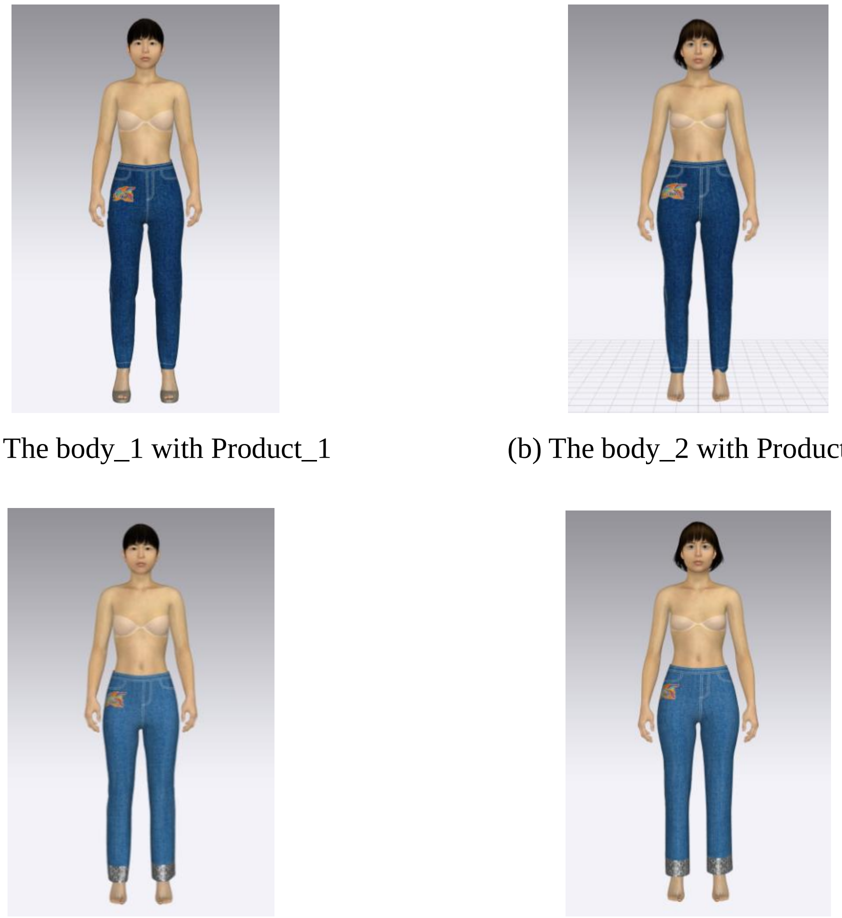
Next, we will show the images of the two body shapes and their fitting effects with the two new products in order to visually validate the results obtained from the recommendation system.

The virtual human bodies are generated from the 3D body scanning measures on the real human bodies by using the CLO 3D software (Figure 5-8).

(a) Virtual human body of body_1 (b) Virtual human body of body_2

Figure 5-8 Two specific virtual human models

Then, the virtual 3D jeans are generated from the parameters of two newly designed real products. The ultimate display results are shown in Figure 5-9.



(a) The body_1 with Product_1 (b) The body_2 with Product_1

(c) The body_1 with Product_2 (d) The body_2 with Product_2

Figure 5-9 Virtual display of new products on different human bodies

5.4.4.2 Recommending of a series of design schemes for a specific body shape and multiple fashion theme levels (Case 2)

The aim of this case is to validate 1) whether the system can recommend suitable design schemes for a specific body shape and specific fashion themes; and 2) whether the system can improve the recommended design schemes by the feedback mechanism or the working cycle of recommendation – virtual product display – evaluation – adjustment.

The input data of this case are given below.

(a) Target population

10 different human bodies (body_1 and body_2 are included) are selected from the target population (young women of 18-25 years in Central China).

(b) The desired fashion theme levels

We make 8 combinations of the levels for three fashion themes as follows.

Fashion Theme 1 (FT1): T_1 = "a little Neuter", T_2 = "a little Elegant", and T_3 = "Neutral"

Fashion Theme 2 (FT2): T_1 = "Neuter", T_2 = "Elegant", and T_3 = "Traditional"

Fashion Theme 3 (FT3): $T_1 =$ “Neuter”, $T_2 =$ “Elegant”, and $T_3 =$ “Modern”

Fashion Theme 4 (FT4): $T_1 =$ “Neuter”, $T_2 =$ “Wild”, and $T_3 =$ “Traditional”

Fashion Theme 5 (FT5): $T_1 =$ “Neuter”, $T_2 =$ “Wild”, and $T_3 =$ “Modern”

Fashion Theme 6 (FT6): $T_1 =$ “Feminine”, $T_2 =$ “Elegant”, and $T_3 =$ “Traditional”

Fashion Theme 7 (FT7): $T_1 =$ “Feminine”, $T_2 =$ “Elegant”, and $T_3 =$ “Modern”

Fashion Theme 8 (FT8): $T_1 =$ “Feminine”, $T_2 =$ “Wild”, and $T_3 =$ “Modern”

In the proposed system, assuming that all the basic styles are related to body shapes, and fabric properties and colors are only related to fashion themes but have no impacts on body shapes and design styles. Therefore, in a design scheme, the fabric and color are only determined by a specific fashion theme.

By using the inference engine, the recommendation system establishes the design ontology automatically. According to this ontology, the system generates the recommended design schemes by using the relational models defined in Chapter 4.

Next, we give an example on recommendation of design schemes related to Fashion theme 1 (FT1: $T_1 =$ “a little Neuter”, $T_2 =$ “a little Elegant”, and $T_3 =$ “Neutral”) for body_1 and body_2. For simplicity, we only give one relevant design scheme for each human body in the following analysis.

For the body_1, the recommended product is product_3 = <style_3, fabric No. 7, color_3>.
For the body_2, the recommended product is product_4 = <style_4, fabric No. 7, color_4>.
where style_3 =

$$(\underset{PATTERN_3}{Straight}, \underset{WAIST_2}{Regular\text{-}Waist}, \underset{LEG_2}{Regular\text{-}Leg}, \underset{DETAIL_{11}}{Crescent\ Front\text{-}Pocket}, \underset{DETAIL_{21}}{Uncovered\ Back\text{-}Pocket},$$

$$\underset{DETAIL_{31}}{Fasteners\ Front\text{-}Fly}, \underset{DETAIL_{41}}{Hidden\ Side\text{-}Seam}, \underset{DETAIL_{51}}{no\text{-}Patchwork}, \underset{DETAIL_{61}}{no\text{-}Holey}, \underset{ACCESSORY_1}{Embroidery}, \underset{ACCESSORY_5}{Embroidery})$$

$$color\_3 = color\_4 = (\underset{HUE_1}{low\text{-}Hue}, \underset{VALUE_1}{low\text{-}Value}, \underset{CHROMA_3}{high\text{-}Chroma})$$

$$style\_4 = (\underset{PATTERN_3}{Straight}, \underset{WAIST_3}{High\text{-}Waist}, \underset{LEG_2}{Regular\text{-}Leg}, \underset{DETAIL_{11}}{Crescent\ Front\text{-}Pocket}, \underset{DETAIL_{21}}{Uncovered\ Back\text{-}Pocket},$$

$$\underset{DETAIL_{31}}{Fasteners\ Front\text{-}Fly}, \underset{DETAIL_{41}}{Hidden\ Side\text{-}Seam}, \underset{DETAIL_{51}}{no\text{-}Patchwork}, \underset{DETAIL_{61}}{no\text{-}Holey}, \underset{ACCESSORY_1}{Embroidery}, \underset{ACCESSORY_5}{Embroidery})$$

By visualizing the virtual products corresponding to the recommended design schemes (Figure 5-10), the evaluator (one designer selected from Group 1) makes an evaluation of virtual fitting effects and expression quality of the fashion theme on the two specific body shapes.


(a) The body_1 with the product_3


(b) The body_2 with the product_4

Figure 5-10 Virtual display of the recommended results for various human bodies

By using the evaluation procedure of Section 5.4.2, the designer is satisfied by the recommended design scheme for body_1, but considers that the level of the fashion theme "Traditional-Modern (T_3)" of the recommended style for body_2 is "a little Traditional" instead of "Neutral", as what he/she expected. Therefore, the recommended style for the body_2 needs to be adjusted according to the expected level for the fashion theme T_3.

In this system, the default value of the maximal number of evolution iterations Th is set to 500 and the default value of the size of the initial population to $n = 10$. By executing the self-adjusting procedure related to the expected level of fashion theme, this system generates a new relational matrix $R^t(S, T_3)$. Then, by using the inference engine, this system recommends a new style below.

style_5 =

$$(\underset{PATTERN_3}{Straight}, \underset{WAIST_3}{High\text{-}Waist}, \underset{LEG_2}{Regular\text{-}Leg}, \underset{DETAIL_{11}}{Crescent\ Front\text{-}Pocket}, \underset{DETAIL_{21}}{Uncovered\ Back\text{-}Pocket},$$

$$\underset{DETAIL_{31}}{Fasteners\ Front\text{-}Fly}, \underset{DETAIL_{41}}{Hidden\ Side\text{-}Seam}, \underset{DETAIL_{51}}{no\text{-}Patchwork}, \underset{DETAIL_{61}}{no\text{-}Holey}, \underset{ACCESSORY_1}{Embroidery})$$

Having introduced the new style style_5 into the system, the recommendation results show that the former levels of the fashion themes T_1 and T_2 are unchanged in the evaluation of the new design scheme. However, the level of the fashion theme T_3 is moved to "$\tilde{F}_3$" (Neutral), showing that the adjusting procedure is efficient. After adjusted one time, this system can successfully recommend a satisfactory design scheme to the designer.

Next, we discuss the statistical performance of the proposed recommendation system in the whole population. From the 103 human models obtained in Chapter 4, we take 10 various body shapes. By combing these body shapes with the previous 8 fashion theme levels, we generate 80 design cases and apply the proposed working cycle of recommendation – virtual product display – evaluation – adjustment. For these different cases, the numbers of iterations for obtaining successful design schemes satisfied by the designer are listed in Table 5-4.

Table 5-4 The number of iterations needed for a successful recommendation

Body shape	FT1	FT2	FT3	FT4	FT5	FT6	FT7	FT8
body_1	1	2	1	1	3	1	1	>3
body_2	2	1	1	2	1	1	>3	1
body_3	1	1	>3	1	1	1	1	1
body_4	1	1	2	1	1	>3	1	2
body_5	1	2	1	3	2	1	1	1
body_6	2	3	1	>3	1	1	1	3
body_7	3	1	1	1	1	2	3	>3
body_8	1	1	1	1	2	1	1	1
body_9	1	1	2	1	>3	1	1	1
body_10	1	2	1	1	3	1	1	2

The above results are obtained from the original design knowledge base (also called permanent knowledge base) which has never been modified by the results of successful recommendation. However, if we integrate these successfully recommended products into the knowledge base, the further recommendation performance will be further improved. The corresponding results are shown in Table 5-5 and Table 5-6.

Table 5-5 The number of iterations needed for a successful recommendation with knowledge updating once (from the first successfully recommended cases without adjustment)

Body shape	FT1	FT2	FT3	FT4	FT5	FT6	FT7	FT8
body_1	1	1	1	1	2	1	1	>3
body_2	1	1	1	1	1	1	>3	1
body_3	1	1	2	1	1	1	1	1
body_4	1	1	1	1	1	>3	1	2
body_5	1	1	1	1	1	1	1	1
body_6	2	3	1	1	1	1	1	1
body_7	1	1	1	1	1	2	3	3
body_8	1	1	1	1	1	1	1	1
body_9	1	1	1	1	>3	1	1	1
body_10	1	2	1	1	1	1	1	2

Table 5-6 number of iterations needed for a successful recommendation with knowledge updating twice (from the two first successfully recommended cases with no more than one adjustment)

Body shape	FT1	FT2	FT3	FT4	FT5	FT6	FT7	FT8
body_1	1	1	1	1	1	1	1	>3
body_2	1	1	1	1	1	1	3	1
body_3	1	1	1	1	1	1	1	1
body_4	1	1	1	1	1	3	1	1
body_5	1	1	1	1	1	1	1	1
body_6	1	2	1	1	1	1	1	1
body_7	1	1	1	1	1	1	2	2
body_8	1	1	1	1	1	1	1	1
body_9	1	1	1	1	3	1	1	1
body_10	1	1	1	1	1	1	1	1

By combing all the above three tables, we obtain the overall statistical results for all design cases of successful recommendation (See Table 5-6).

Table 5-7 Statistical rates for all cases of successful recommendation

	1st recommendation	2nd recommendation	3rd recommendation	Accumulated rate of success
Original knowledge	66.25%	16.25%	8.75%	91.25%
Knowledge updating once	82.50%	8.75%	3.75%	95.00%
Knowledge updating twice	91.25%	3.75%	3.75%	98.75%

From Table 5-7, we can find that the rates of recommendation success are rather high for all design cases. Most of successful cases are determined just after performing the first recommendation without adjustment. The adjustment procedure can effectively improve the rate of success for the second and third recommendations. The successive updating of the design knowledge base can clearly improve the quality of recommendation. From these results, the capacities of recommendation and knowledge learning in the proposed recommendation system can be validated effectively.

5.5 Conclusion

According to the relational models proposed in Chapter 4, we set up the ontology model of garment design and present the ontology-based design knowledge base in this chapter. On this basis, we develop the designer-oriented recommendation system with feedback and self-adjusting function.

The proposed recommendation system can generate design schemes rapidly for a specific body shape and a desired fashion theme. And the recommended results can be adjusted automatically according to the feedback from the designer' evaluation on virtual products until the designer' satisfaction. Therefore, we believe that the proposed recommendation system can progressively integrate the knowledge of designers and improve the efficiency of the design process for personalized garments by handling this knowledge base.

The performance of the proposed system has been successfully validated by two real cases, i.e. examination of new designed products and recommendation of design schemes.

GENERAL CONCLUSION AND PERSPECTIVES

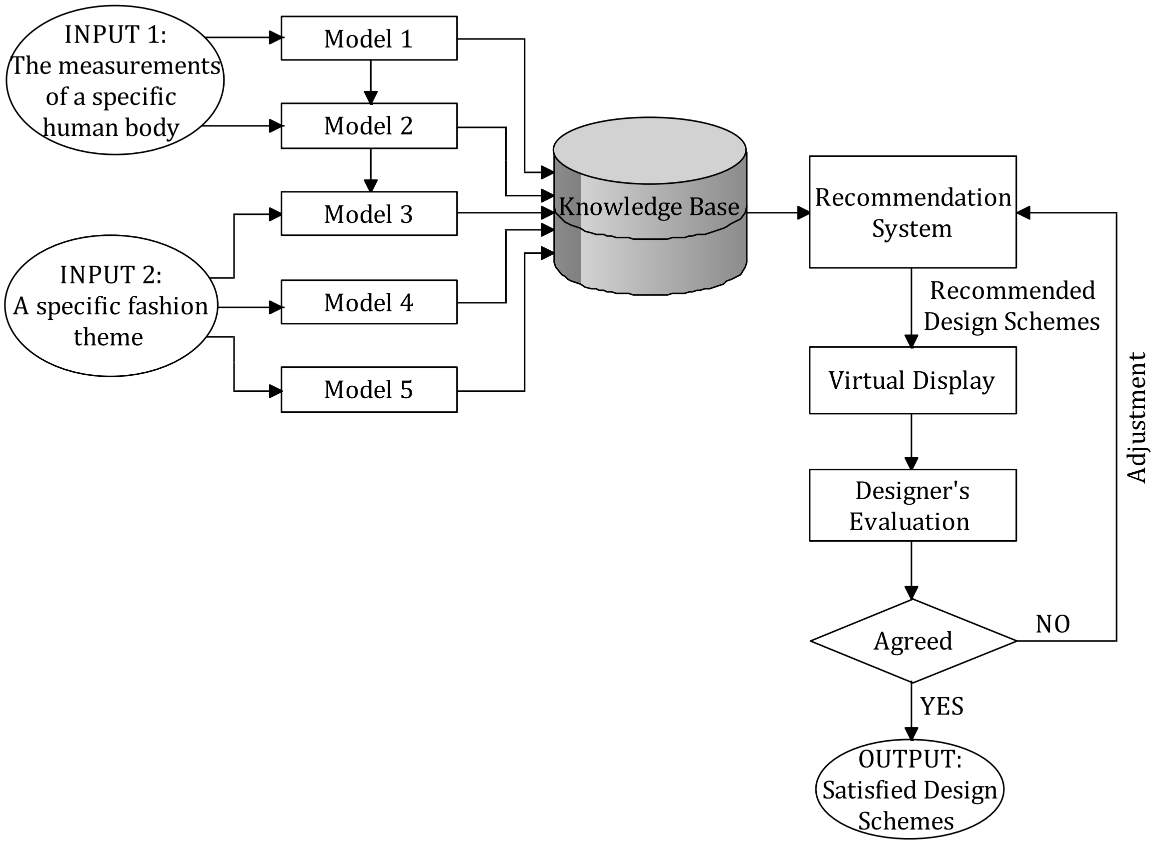


Figure 6-1 The general scheme of my thesis

In current fashion markets, consumer's personalized requirements are more and more increasing, and then realization of personalized fashion design with low cost and quick reactivity has become a key to success for many apparel enterprises. In this context, development of designers' knowledge-based personalized recommendation systems appears extremely significant, because they can effectively reduce the complexity of designers' work by making a series of selections and evaluations and easily handling different design resources (human body shapes, design styles, fabrics, …). In my thesis, based on the design knowledge acquisition from designers by using a series of sensory evaluation procedures, we propose a designer-oriented intelligent recommendation system for helping fashion designers to determine optimal design schemes in terms of personalized body shapes and fashion theme requirements.

The general structure of the proposed recommendation system is summarized in Figure

6-1. It is based on the design knowledge base, composed of 5 models and related rules (from Model 1 to Model 5), permitting to classify human body shapes for a target population and characterize the relations between human body shapes, desired fashion themes and design schemes (styles, colors, fabrics). These models have been built by learning from data acquired from a set of physical (3D human body measurements and fabric technical parameters) and sensory experiments (perception on body shapes, sensory properties of fabrics, relations between body positions and basic style elements, and between fashion themes and colors and fabrics). The fuzzy techniques (fuzzy classification, fuzzy relations, similarity measures) and rough sets constitute the main computational tools in these modeling procedures. The overall garment design knowledge structure is formally expressed using an ontology model (Model 6), associated with the previous data learning-based models. An ontology-based inference procedure is built by successively applying these data learning-based models for generating a list of relevant garment products. Moreover, the proposed recommendation system has a mechanism of feedback and self-learning or self-adjustment. This feedback mechanism enables to realize human-computer interactions via sensory evaluations on the fitting of recommended 3D virtual garments on the specific consumer's body shape. If the 3D virtual fitting effect of the current recommended design scheme is not satisfied by the designer, two other data learning-based algorithms will be applied in order to automatically adjust the design knowledge base by using a genetic algorithm and recommend new design schemes. The proposed cycle of recommendation, i.e. design scheme recommendation – 3D virtual garment generation and virtual fitting – sensory evaluation – knowledge base adjustment, will be repeated until the designer's satisfaction. The proposed recommendation system has been validated through two real design cases.

The main contributions of my thesis can be summarized as follows.

1) Classification of body shapes by combining both body measurements and human perception. Compared with classical body measures-based classification algorithms, the proposed method is more robust, more interpretable and closer to designer's human perception-based working processes.

2) Representation and computation of evaluation results of different evaluators by using fuzzy distributions without making direct data aggregation. The proposed method can make the evaluation results more accurate and robust, and effectively reduce the impacts of weights, often appearing in a classical data fusion procedure.

3) Establishment of a design knowledge base, in which the classically separated design knowledge is structured and formally represented by an ontology model, which can largely

help to generate feasible design schemes.

4) Development of a feedback and self-adjustment mechanism. The classical recommendation systems only provide recommended products to users without considering whether they are accepted or not. The proposed feedback mechanism can adjust the knowledge base automatically by a self-learning algorithm according to the users' feedback. In this context, the proposed recommendation system is directly involved in the new design process of personalized garment products. The new design process is strongly associated with human-machine interactions and supported by the resources of the professional design knowledge base, which will be progressively enhanced by learning from new design cases.

The current work can still be improved and perfected in many aspects. In the future research, we expect to make more efforts in the following orientations.

1) "Human" is the subject of garment. For better realizing personalized garment design, it is necessary to make the most efforts to be adapted to the human requirements of fitting, comfort and health in garment design. Therefore, **"Human-Garment-Environment" should be fully taken into account.** For simplicity, we only consider human dimensions in my thesis. In fact, the classification of human bodies can be further improved based on more physical indices such as skin color and face features, and socio-cultural factors such as wearing preferences, emotions and professions. In addition, some natural environment factors including season, temperature, humidity, and social environment such as politics and economy, should be considered.

2) In the proposed models, only the relations between fashion themes and the three design factors (design styles, colors and fabrics) are concerned. The relations between all the design factors can be analyzed by using a complex network model.

3) The fuzzy distributions of evaluation results can be further analyzed in the future research so as to improve the current knowledge-based models.

4) Since the amount of data is very limited in our research, we can just set up the data-based models and the knowledge base is just applicable to a specific type of garment products for a specific target population. For dealing with more data in an open environment, we need to improve the concerned models so that they become more flexible and capable of solving data conflicts effectively.

5) In our research, the recommended design schemes are displayed using the corresponding virtual products, permitting to save design time and costs largely. However, there still exist gaps between real and virtual garments. Therefore, we need to control the relations of real and virtual fitting displays in order to obtain more accurate evaluation results.

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Appendix 1 Human body measurements - Experiment 1

The index values of the parts of the body shapes:

Body samples	Waist	Hip			Abdomen			Leg		Thigh			Calf		
	WS	hs_1	hs_2	hs_3	as_1	as_2	as_3	ll_1	ll_2	ts_1	ts_2	ts_3	cs_1	cs_2	cs_3
1	0.4364	19.0000	1.2639	0.5515	6	1.0833	0.4727	0.4242	0.5879	0.6944	0.5495	0.3030	0.4583	0.3626	0.2000
2	0.4465	15.0000	1.2113	0.5409	16	1.2254	0.5472	0.4591	0.5975	0.6197	0.5116	0.2767	0.4930	0.4070	0.2201
3	0.4125	30.0000	1.4545	0.6000	1	1.0152	0.4188	0.4688	0.6063	0.7879	0.5417	0.3250	0.5455	0.3750	0.2250
4	0.4817	17.0000	1.2152	0.5854	9	1.1139	0.5366	0.5061	0.6646	0.6329	0.5208	0.3049	0.4177	0.3438	0.2012
5	0.4304	22.0000	1.3235	0.5696	8	1.1176	0.4810	0.5253	0.6519	0.6912	0.5222	0.2975	0.4559	0.3444	0.1962
6	0.4024	25.0000	1.3788	0.5549	15	1.2273	0.4939	0.5122	0.6280	0.6818	0.4945	0.2744	0.5000	0.3626	0.2012
7	0.4088	17.0000	1.2615	0.5157	15	1.2308	0.5031	0.4717	0.6289	0.8000	0.6341	0.3270	0.4769	0.3780	0.1950
8	0.4375	20.0000	1.2857	0.5625	11	1.1571	0.5063	0.4938	0.6125	0.7143	0.5556	0.3125	0.4714	0.3667	0.2063
9	0.4430	20.0000	1.2857	0.5696	9	1.1286	0.5000	0.4684	0.6076	0.7143	0.5556	0.3165	0.4571	0.3556	0.2025
10	0.4410	20.0000	1.2817	0.5652	11	1.1549	0.5093	0.4969	0.6087	0.6901	0.5385	0.3043	0.4789	0.3736	0.2112
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
115	0.3774	35.0000	1.5833	0.5975	9	1.1500	0.4340	0.4528	0.5660	0.6333	0.4000	0.2390	0.5333	0.3368	0.2013
116	0.3974	35.0000	1.5645	0.6218	9	1.1452	0.4551	0.4103	0.6090	0.7903	0.5052	0.3141	0.6129	0.3918	0.2436
117	0.3882	22.0000	1.3729	0.5329	5	1.0847	0.4211	0.3750	0.6579	0.7119	0.5185	0.2763	0.4407	0.3210	0.1711
118	0.3929	34.0000	1.5152	0.5952	14	1.2121	0.4762	0.4524	0.5655	0.7576	0.5000	0.2976	0.6061	0.4000	0.2381
119	0.3750	35.0000	1.5833	0.5938	5	1.0833	0.4063	0.4813	0.6250	0.7500	0.4737	0.2813	0.5833	0.3684	0.2188
120	0.3924	20.0000	1.3226	0.5190	8	1.1290	0.4430	0.4684	0.5949	0.6935	0.5244	0.2722	0.5000	0.3780	0.1962
121	0.4000	23.0000	1.3382	0.5353	18	1.2647	0.5059	0.4765	0.6235	0.7059	0.5275	0.2824	0.5000	0.3736	0.2000
122	0.4072	26.0000	1.3824	0.5629	6	1.0882	0.4431	0.4671	0.6467	0.7647	0.5532	0.3114	0.4853	0.3511	0.1976
123	0.4182	23.0000	1.3333	0.5576	12	1.1739	0.4909	0.4727	0.6000	0.7391	0.5543	0.3091	0.5217	0.3913	0.2182
124	0.4625	10.0000	1.1351	0.5250	2	1.0270	0.4750	0.4125	0.5063	0.5135	0.4524	0.2375	0.3649	0.3214	0.1688
125	0.4167	30.0000	1.4286	0.5952	20	1.2857	0.5357	0.5595	0.6786	0.8571	0.6000	0.3571	0.6429	0.4500	0.2679

Appendix 2 The technical parameters of denim fabric samples - Experiment 2

No.	Fiber Composition (%)	Gram-Weight (g/m^2)	Thickness (mm)	Density (a yarn/10cm)		Breaking-Load (N)		Elongation (%)		moisture – permeability ($g/m^2 \cdot h$)	air-permeability (mm/s)	Test Aperture (mm)
				warp	weft	warp	weft	warp	weft			
1	Cotton: 71.7 Polyester: 25.6 Spandex: 2.7	409	0.83	394.0	223.9	825	502	17.4	23.4	321	45.33	2
7	Cotton: 47.3 Polyester: 31.7 Viscose: 18.0 Spandex: 3.0	323	0.57	430.0	304.0	594	685	19.7	14.1	363	44.76	2
8	Cotton: 46.0 Polyester: 31.2 Viscose: 18.2 Spandex: 4.6	348	0.61	448.0	296.0	999	670	16.1	22.0	421	40.87	2
9	Cotton: 100	415	0.73	290.0	208.0	922	480	15.7	7.4	392	42.4	2
11	Cotton: 72.6 Polyester: 7.1 Viscose: 19.6 Spandex: 0.7	269	0.49	540.0	187.7	798	386	5.7	10.1	515	77.63	2
13	Cotton: 69.6 Polyester:7.6 Viscose:22.1 Spandex: 0.7	327	0.79	581.6	205.8	279	895	11.0	11.2	443	81.65	2
14	Lyocell: 100	290	0.37	398.0	253.8	506	438	8.1	5.1	405	439.62	4
16	Cotton: 35.7 Lyocell: 64.3	182	0.39	400.0	205.4	383	397	6.5	7.7	423	412.91	6
18	Cotton: 96.1 Spandex: 3.9	385	0.64	402.0	143.8	1275	306	13.9	11.6	296	31.62	1.2
22	Cotton:63.9 Polyester:33.8 Spandex: 2.3	247	0.43	504.3	209.4	666	471	15.3	23.0	406	23.75	1.2
23	Viscose:37.3 Cotton: 34.3 Polyester:26.0 Spandex:2.4	353	0.74	621.3	337.7	784	362	14.6	28.4	338	37.25	1.2

The related Chinese Nation Textile Standard and the apparatuses used in our experiment below.

(1) Fiber Composition: FZ/T 01053, FZ/T 01057 (Apparatus: Cu-2 Fiber Measurer)

(2) Gram-Weight and Thickness: GB/T 4669-2008 (Apparatus: AL204 Analytical Balance, YG141D Digital Fabric Thickness Measurer)

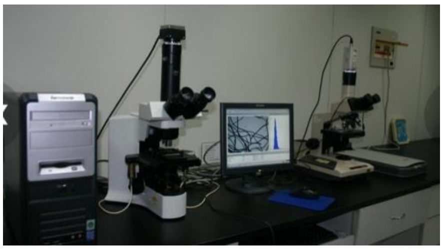
(3) Density: GB/T 4668-1995 (Apparatus: CU-MD Density Measurer)

(4) Breaking-Load and Fracture-Elongation: GB/T 3923-2013 (Apparatus: AGS-J Electronic Universal Strength Tester)

(5) Moisture-Permeability: GB/T 12704.1-2009 (Apparatus: DH-450 Water Vapor Permeability Testing Apparatus)

(6) Air-Permeability: GB/T 5453-1997 (Apparatus: YG461//Ⅱ Digital Air-Permeability Testing Apparatus)

Measuring Apparatus



(a) Cu-2 Fiber Measurer

(b) CU-MD Density Measurer

(c) YG141D Digital Fabric Thickness Measurer

(d) AL204 Analytical Balance

(e) AGS-J Electronic Universal Strength Tester

(f) DH-450 Water Vapor Permeability Testing Apparatus

(g) YG461 Digital Air-Permeability Testing Apparatus

Appendix 3 Results of sensory experiments

(1) The parts of sensory results on the shapes of six lower body positions -- Experiment 3

No.	Waist	Hip	Abdomen	Leg length	Thigh	Calf	No.	Waist	Hip	Abdomen	Leg length	Thigh	Calf
1	*M*	*M*	*M*	*S*	*M*	*S*	93	*S*	*L*	*M*	*L*	*M*	*M*
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
33	*M*	*L*	*M*	*S*	*S*	*M*	101	*S*	*L*	*S*	*M*	*L*	*L*
35	*M*	*M*	*S*	*L*	*S*	*S*	103	*S*	*M*	*S*	*M*	*M*	*L*
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
54	*S*	*S*	*S*	*S*	*VS*	*L*	114	*S*	*M*	*S*	*M*	*S*	*M*
56	*M*	*S*	*M*	*M*	*S*	*M*	116	*VS*	*L*	*VS*	*M*	*L*	*M*
⋮	⋮	⋮	⋮	⋮	⋮	⋮	118	*S*	*VL*	*M*	*VS*	*VS*	*L*
91	*M*	*M*	*VS*	*S*	*M*	*M*	⋮	⋮	⋮	⋮	⋮	⋮	⋮
⋮	⋮	⋮	⋮	⋮	⋮	⋮	124	*M*	*L*	*M*	*M*	*M*	*S*

(2) The sensory evaluation on the relation between the shapes of various body positions and basic style elements -- Experiment 4

BS	$PATTERN_1$	$PATTERN_2$	$PATTERN_3$	$PATTERN_4$	$WAIST_1$	$WAIST_2$	$WAIST_3$	LEG_1	LEG_2	LEG_3	LEG_4
$WS^{(VS)}$	1	-1	0	1	-1	1	-1	-1	1	0	0
$WS^{(S)}$	1	-1	1	1	-1	1	-1	-1	1	1	0
$WS^{(M)}$	1	0	1	0	1	1	1	1	1	1	1
$WS^{(L)}$	-1	1	1	0	1	1	1	1	1	1	0
$WS^{(VL)}$	-1	0	1	0	0	0	0	1	1	1	-1
$HS^{(VS)}$	0	1	0	0	1	1	1	1	1	1	1
$HS^{(S)}$	1	1	0	0	1	1	1	1	1	1	1
$HS^{(M)}$	0	1	1	0	1	1	1	1	1	0	1
$HS^{(L)}$	-1	0	1	1	0	0	0	0	1	0	1
$HS^{(VL)}$	0	0	1	1	0	0	0	0	0	0	-1
$AS^{(VS)}$	0	1	0	1	0	0	0	0	0	0	0
$AS^{(S)}$	0	1	0	1	0	0	0	1	0	1	0
$AS^{(M)}$	0	-1	0	1	0	0	0	1	0	0	1
$AS^{(L)}$	0	-1	1	0	1	0	1	0	1	0	0
$AS^{(VL)}$	1	1	1	0	1	0	1	0	0	0	0
$LL^{(VS)}$	1	1	1	0	1	1	0	1	1	1	1
$LL^{(S)}$	1	1	1	1	0	1	0	1	1	1	1
$LL^{(M)}$	1	1	0	1	0	0	1	1	1	0	1
$LL^{(L)}$	0	0	0	0	0	0	1	0	1	-1	0
$LL^{(VL)}$	0	-1	0	0	0	0	1	0	0	-1	0
$TS^{(VS)}$	-1	0	0	0	0	0	0	0	0	0	0
$TS^{(S)}$	0	0	1	0	0	0	0	0	0	0	0
$TS^{(M)}$	0	0	1	0	0	1	0	0	1	1	0
$TS^{(L)}$	1	1	0	0	1	1	1	1	1	0	0
$TS^{(VL)}$	0	1	0	0	0	1	1	1	0	0	0
$CS^{(VS)}$	-1	-1	0	0	0	0	0	-1	0	0	0
$CS^{(S)}$	0	0	1	0	0	0	0	0	0	0	0
$CS^{(M)}$	0	0	1	0	0	0	0	0	1	1	0
$CS^{(L)}$	1	1	0	0	1	1	1	1	1	1	0
$CS^{(VL)}$	0	1	0	0	1	1	0	1	0	0	0

(3) The sensory evaluation on the relation between fashion themes and style elements -- Experiment 5

Style elements	Neuter - Feminine	Elegant - Wild	Traditional - Modern
$PATTERN_1$	-1	1	1
$PATTERN_2$	0	0	1
$PATTERN_3$	0	0	-1
$PATTERN_4$	0	0	-1
$WAIST_1$	2	2	1
$WAIST_2$	-1	-1	-2
$WAIST_3$	-1	-1	0
LEG_1	1	0	0
LEG_2	-2	0	0
LEG_3	0	0	0
LEG_4	-1	0	0
$DETAIL_1$	0	0	0
$DETAIL_2$	0	0	0
$DETAIL_3$	1	0	0
$DETAIL_4$	0	0	0
$DETAIL_5$	0	0	0
$DETAIL_6$	0	0	-1
$DETAIL_7$	-2	-1	-1
$DETAIL_8$	1	1	1
$DETAIL_9$	1	1	0
$DETAIL_{10}$	0	0	0
$DETAIL_{11}$	2	3	1
$DETAIL_{12}$	-1	-1	-1
$ACCESSORY_0$	1	0	0
$ACCESSORY_1$	0	-1	0
$ACCESSORY_2$	0	-1	0
$ACCESSORY_3$	0	-1	0
$ACCESSORY_4$	1	1	0
$ACCESSORY_5$	0	-1	0
$ACCESSORY_6$	2	2	0

(4) The sensory evaluation on the relation between fashion themes and color properties (The numbers of people) -- Experiment 6

Color perception	Neuter - Feminine	Elegant - Wild	Traditional - Modern
Cold Hue	1	-2	2
Middle Hue	-2	0	-1
Warm Hue	-1	1	-1
Low Value	-1	0	3
Middle Value	-1	-1	0
High Value	1	0	-1
Low Chroma	1	1	2
Middle Chroma	-1	0	0
High Chroma	1	1	0

(5) The sensory evaluation of fabric samples -- Experiment 7

Fabric Sample No.	sp_1	sp_2	sp_3	sp_4	sp_5
1	$\tilde{F}_5$	$\tilde{F}_6$	$\tilde{F}_3$	$\tilde{F}_5$	$\tilde{F}_6$
7	$\tilde{F}_4$	$\tilde{F}_4$	$\tilde{F}_4$	$\tilde{F}_6$	$\tilde{F}_3$
8	$\tilde{F}_6$	$\tilde{F}_5$	$\tilde{F}_6$	$\tilde{F}_5$	$\tilde{F}_5$
9	$\tilde{F}_7$	$\tilde{F}_7$	$\tilde{F}_2$	$\tilde{F}_3$	$\tilde{F}_7$
11	$\tilde{F}_5$	$\tilde{F}_3$	$\tilde{F}_7$	$\tilde{F}_1$	$\tilde{F}_2$
13	$\tilde{F}_2$	$\tilde{F}_5$	$\tilde{F}_7$	$\tilde{F}_7$	$\tilde{F}_2$
14	$\tilde{F}_1$	$\tilde{F}_1$	$\tilde{F}_5$	$\tilde{F}_1$	$\tilde{F}_1$
16	$\tilde{F}_1$	$\tilde{F}_3$	$\tilde{F}_5$	$\tilde{F}_2$	$\tilde{F}_2$
18	$\tilde{F}_5$	$\tilde{F}_6$	$\tilde{F}_4$	$\tilde{F}_4$	$\tilde{F}_5$
22	$\tilde{F}_6$	$\tilde{F}_5$	$\tilde{F}_6$	$\tilde{F}_2$	$\tilde{F}_6$
23	$\tilde{F}_3$	$\tilde{F}_3$	$\tilde{F}_3$	$\tilde{F}_7$	$\tilde{F}_5$
24	$\tilde{F}_3$	$\tilde{F}_2$	$\tilde{F}_3$	$\tilde{F}_3$	$\tilde{F}_5$

(6) The sensory evaluation of the relationship between fashion themes and sensory properties of fabrics -- Experiment 8

Sensory property	Fashion theme T_1						
	extreme Neuter	Neuter	a little Neuter	neutral	a little Feminine	Feminine	extreme Feminine
extreme Soft							√
Soft						√	
a little Soft					√		
neutral				√			
a little Hard			√				
Hard		√					
extreme Hard	√						
extreme Smooth							√
Smooth						√	
a little Smooth					√		
neutral				√			
a little Rough			√				
Rough		√					
extreme Rough	√						
extreme Wrinkle-Resistant		√					
Wrinkle-Resistant			√				
a little Wrinkle-Resistant				√			
neutral				√			
a little Crumply			√				
Crumply			√				
extreme Crumply				√			
extreme Cool	√						
Cool		√					
a little Cool			√				
neutral				√			
a little Warm					√		
Warm						√	
extreme Warm							√
extreme Draped							√
Draped						√	
a little Draped					√		
neutral				√			
a little non-Draped			√				
non-Draped		√					
extreme non-Draped	√						

Sensory property	Fashion theme T_2						
	extreme Elegant	Elegant	a little Elegant	neutral	a little Wild	Wild	extreme Wild
extreme Soft				√			
Soft				√			
a little Soft		√					
neutral			√				
a little Hard					√		
Hard						√	
extreme Hard							√
extreme Smooth	√						
Smooth		√					
a little Smooth			√				
neutral				√			
a little Rough					√		
Rough						√	
extreme Rough							√
extreme Wrinkle-Resistant		√					
Wrinkle-Resistant			√				

a little Wrinkle-Resistant					√		
neutral				√			
a little Crumply					√		
Crumply						√	
extreme Crumply							√
extreme Cool							√
Cool						√	
a little Cool					√		
neutral				√			
a little Warm				√			
Warm			√				
extreme Warm			√				
extreme Draped	√						
Draped		√					
a little Draped			√				
neutral				√			
a Little non-Draped					√		
non-Draped						√	
extreme non-Draped							√

Sensory property	Fashion theme T_3						
	extreme Traditional	Traditional	a little Traditional	neutral	a little Modern	Modern	extreme Modern
extreme Soft				√			
Soft				√			
a little Soft					√		
neutral			√				
a little Hard			√				
Hard		√					
extreme Hard	√						
extreme Smooth						√	
Smooth					√		
a little Smooth					√		
neutral				√			
a little Rough			√				
Rough					√		
extreme Rough						√	
extreme Wrinkle-Resistant				√			
Wrinkle-Resistant			√				
a little Wrinkle-Resistant			√				
neutral				√			
a little Crumply					√		
Crumply						√	
extreme Crumply							√
extreme Cool							√
Cool						√	
a little Cool					√		
neutral				√			
a little Warm			√				
Warm		√					
extreme Warm	√						
extreme Draped							√
Draped						√	
a little Draped					√		
neutral				√			
a Little non-Draped			√				
non-Draped			√				
extreme non-Draped		√					