N° d'ordre : 40817 Année 2012

THÈSE
présentée à

L'UNIVERSITÉ DES SCIENCES ET TECHNOLOGIES DE LILLE

ÉCOLE DOCTORAL DES SCIENCES POUR L'INGÉNIEUR

en vue de l'obtention du titre de Docteur dans la spécialité
Automatique, Génie Informatique, Traitement du Signal et des Images

par
Lichuan WANG

Contribution to Development of an Intelligent System for Supporting Personalized Fashion Design

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

Soutenue le 16 mai 2012

JURY

Luigi LANCIERI	Professeur, USTL, Villeneuve d'Ascq	Président du Jury
Yan CHEN	Professeur, Université de Soochow, Suzhou	Rapporteur
Carole BOUCHARD	Maître de conférence & HDR, ENSAM, Paris	Rapporteur
Alexandra DE RAEVE	Professeur, University College Ghent, Ghent	Examinatrice
Xianyi ZENG	Professeur, ENSAIT, Roubaix	Directeur
Ludovic KOEHL	Professeur, ENSAIT, Roubaix	Co-directeur

Contribution to Development of an Intelligent System for Supporting Personalized Fashion Design

Abstract

Mass customization has been applied in fashion mass market for more than 20 years. However, the related work mainly focuses on application of CAD tools such as body shape modeling and garment modeling. Fashion design and fashion marketing have not been involved systematically. In fact, when developing mass customized products, we should study human perception on products, including consumer's and design expert's perception, and integrate it into the new process of design.

In my PhD research project, we originally propose a fashion decision support system for supporting designer's work. In this system, we first characterize and acquire fashion expert perception and consumer perception on human body shapes. Two experiments are proposed in order to acquire expert perceptual data (sensory descriptors) on naked virtual body shapes and those with garment design styles. Another experiment is carried out for acquiring consumer perceptual data on relations between fashion themes (images desired by general public) and sensory descriptors. Next, these perceptual data are formalized and analyzed using the intelligent techniques, i.e. fuzzy set theory, decision tree and fuzzy cognitive map. The complex relations between these perceptions as well as the physical measurements of body shapes are modeled, leading to compute the relevancy degrees of a naked body and a body with a garment design style to a given fashion theme. The comparison of these two relevancy degrees will permit to determine if a new design style is feasible or not for a given fashion theme. The proposed system has been tested and analyzed in two real cases: i.e. customized design and mass market selection.

Key Words: Fashion Design; Human Perception; Intelligent System; Fuzzy sets; Decision Tree; Fuzzy Cognitive Map; Mass Customization

Contribution au développement d'un système intelligent d'aide à la création de styles personnalisés

Résumé

La mass customisation a été appliquée au marché de grande consommation de vêtements depuis plus de 20 ans. Pourtant, les travaux concernés se focalisent essentiellement sur le prototypage virtuel par utilisation des outils de CAO. Le stylisme et le marketing n'ont pas été étudiés de façon systématique.

Dans le cadre de ma thèse doctorale, nous proposons un système d'aide à la décision orienté vers les styles afin de fournir des conseils aux créateurs. Dans ce système, nous caractérisons, d'abord, les perceptions de créateurs et de consommateurs sur les morphotypes. Deux expériences ont été effectuées afin d'acquérir les données des experts (descripteurs sensoriels) décrivant les corps virtuels sans et avec styles de vêtements. Une autre expérience a été réalisée pour extraire les données des consommateurs sur les relations entre les thèmes (images socioculturelles souhaités) et les descripteurs sensoriels. Ensuite, ces données perceptuelles sont formalisées et analysées par utilisation des ensembles du flou, des arbres de décision, et des cartes cognitives floues. La modélisation des relations entre ces perceptions et les mensurations du corps permettent de calculer les degrés de pertinence d'un corps humain sans et avec style de vêtement par rapport à un thème spécifique. La comparaison de ces deux degrés de pertinence permet de déterminer si un nouveau style de création est faisable pour un thème donné. Le système proposé a été testé et analysé dans deux cas réels : la création des styles personnalisés et la sélection des styles pour un marché de grande consommation.

Mots clés : Création de styles; Perception Humaine; Système Intelligent; Ensembles Flous; Arbre de Décision; Carte Cognitive Floue; Mass Customisation

Remerciements

Le travail présenté dans ce mémoire a été réalisé au sein du laboratoire GEMTEX de l'ENSAIT (Ecole Nationale Supérieure des Arts et Industries Textiles) à Roubaix. Ce travail m'a permis de démontrer l'intérêt du développement d'un système intelligent d'aide à la création de styles personnalisés.

Je tiens à exprimer toute ma reconnaissance à mon directeur de recherche, Monsieur Xianyi ZENG, Professeur à l'ENSAIT pour m'avoir fait confiance, dirigé et soutenu tout au long de ma thèse. Ses conseil et ses encouragements bienveillants m'ont été très précieux pour accomplir mon travail et rédiger ce mémoire.

Je remercie vivement Monsieur Ludovic KOEHL, Professeur à l'ENSAIT, pour avoir supervisé cette thèse avec un regard critique et prodigué des conseils avisés. Ses connaissances et sa générosité m'ont permis de découvrir le monde magnifique de l'évaluation sensorielle.

Ma grande gratitude va aussi à Monsieur Pascal BRUNIAUX, Professeur à l'ENSAIT, pour sa ponctualité, son efficacité et ses conseils utiles à la réalisation du travail expérimental.

Je tiens aussi à remercier Monsieur Luigi LANCIERI, Professeur à USTL (Université des Sciences et Technologies de Lille), pour avoir accepté de présider la commission d'examen du jury. Je remercie plus particulièrement Madame Yan CHEN, Professeur à l'Université de Soochow, et Madame Carole BOUCHARD, Mâtre de Conférence & HDR à ENSAM (Ecole Nationale Supérieure d'Arts et Métiers), pour accepté d'être les rapporteurs de cette étude. Leurs commentaires m'ont aidé à améliorer la forme de mon travail de recherche et je les en remercie vivement. Mes remerviements vont également à Madame Alexandra DE RAEVE, Professeur à University College Ghent, pour avoir accepté d'être l'examinateur et de participer au jury, ce qui est pour moi un grand honneur.

J'adresse tout spécialement mes remerciements à CSC (China Scolarship Council), pour avoir supporté financièrement cette thèse.

Je remercie aussi tous les ex-thésards et thésards de mezzanine du GEMTEX qui m'ont encouragé, soutenu et avec lesquels j'ai passé de vrais moment de bonheur. Je remercie donc particulièrement Xiaoguang DENG, Yijun ZHU, Xuyuan TAO, Xiao CHEN, Gaurav AGARWAL, Aurélie CAYLA, Jianli LIU, Marion AMIOT, Awe Soronfe DOUMBIA, Gwladys BENISTANT, Claire GRELAKOZSKI, Zhebin XUE, Songxue SHA, Stojanka GRELAKOWSKI, Jana MORCE, Ayham ALRUHBAN, Ahmed Rashed LABANIEH, Vanessa PASQUET, Ludivine MEUNIER, Munir ASHRAF, Nizar DIDANE, Senem KURSUN, Saad NAUMAN, Jonas BOUCHARD, Jérôme VILFAYEAU, Benjamin ALLART et etc.

Bien sûr, la liste ne serait pas complète si je ne remerciais pas mes copaines et copines qui m'ont accompagné durant ces trois années d'étude en France : Huaqiang SHU, Wei GU, Siliang TAN, Paul JEZRAOUI, Cheryl Lobb DE RAHMAN, Wen DENG, Jiahui ZHOU, Dakun LIU, Jinwei DU et etc.

Je tiens enfin à remercier mes parents qui m'ont encouragé à relever le défi de réaliser une thèse en france, le pays « romantique » mais dont la langue et la culture m'étaient inconnues. Je termine en remerciant infiniment à ma fiancée, Zhiyi PAN, pour toute la patience et l'amour qu'elle m'a témoigné durant toute ma période de thèse.

à mes parents et Zhiyi

Contents

List of Figure

List of Table

General Introduction

In modern apparel industry, faced to serious competitions due to globalization, diversification of markets and digital revolution, product designers and managers need to pay much more attention to consumer’s personalized needs in order to quickly submit new products to the markets. Even in mass market, consumers lose their tolerance for regular products and become more and more demanding for special products meeting their individual expectations. They desire to personalize the style, fit and other characters of fashion products. For copying with this new challenge from consumers, fashion companies are more and more interested by the concept of mass customization, i.e. quick design and production of personalized products with low costs similar to those of mass products.

Mass customization has been applied in fashion mass market for more than 20 years. The two main development trends include virtual reality-based personalized prototyping and optimization of the supply chain organization for diversified products. In order to make fashion products more adapted to personalized body shapes, 3D body scanning technology has been used to acquire precise physical body measurements and construct the appropriate visual model for the concerned body shape. Another popular technology is the 3D virtual try-on simulation. It can be used to provide vivid and personalized try-on illustration to online consumers. The 3D virtual try-on technology can also offer an advanced 3D designing environment for fashion designers by largely decreasing the number of real prototypes. In this situation, designers can effectively reduce time and cost in the cycle of new product development.

However, mass customization in fashion industry mainly focuses on application of CAD tools such as body shape modeling and garment modeling and simulation. The concepts of fashion design and fashion marketing have not been studied systematically in this context. In fact, when developing mass customization-oriented design and marketing concepts, we should study human perception on products, including consumer’s and design expert’s perception, and integrate it into the new process of design. The key problems of this study include: extraction and modeling of human perceptual information on products, analysis and modeling of the knowledge and cognition on design and marketing, and decision making for selecting the most appropriate products.

In my PhD research project, we propose a new mass customization-oriented and human perception-based decision support system for supporting designer's work. In this system, the techniques of sensory evaluation are used to extract data from design experts on the basic sensory attributes of human body shapes. These data are independent of any socio-cultural context. In the same time, consumer's perception on relations between the basic sensory attributes of body shapes and the concerned fashion theme are also evaluated. These consumer's data are strongly related to a socio-cultural context. A fashion theme such as 'sporty' and 'professional' can be considered as a social image desired by the consumer and orientation of new design. During the design process, designers should make efforts to reduce the gap between the naked body shape of the consumer and the desired fashion theme by proposing to him/her new appropriate personalized garments.

In the proposed fashion design support system, the techniques of artificial intelligence constitute the main computational tools for formalization and modeling of perceptual data. Especially, fuzzy techniques play an important role in the modeling of this system. The perceptual data of consumers and designers are formalized mathematically using fuzzy sets and fuzzy relations. Moreover, the complex relation between human body measurements and basic sensory attributes, provided by designers, is modeled using a decision tree. And the complex relation between basic sensory attributes and fashion themes, given by consumers, is modeled using a fuzzy cognitive map. The former is an empirical model based on learning data measured and evaluated on a set of representative samples. The latter is a conceptual model obtained from cognition of consumers. The combination of the two previous models can provide more complete information to the fashion design support system, permitting to evaluate a specific body shape related to a desired fashion theme and obtain the design orientation in order to improve the image of the body shape.

In this thesis, our study focuses on the implementation of one part of the entire design support system, i.e. study of the relationship between garment styles and human body shapes.

Skin colors，face, and other issues are not discussed here. Moreover, at experimental level, male overcoat design is used as an example for providing real data to the proposed system and validating the final results. The thesis is organized as follows.

Context of study (Chapter 1)

We present the key backgrounds of the nature of fashion, the process of fashion design, the function of fashion marketing and the current state of mass customization in fashion industry. Especially, the necessity of providing an intelligent conceptual support to fashion mass customization is explained. Finally, the basic principle and general scheme of the proposed fashion design support system is given.

Human perceptual data acquisition (Chapter 2)

The notion and features of human perception are described according to the perceptual processes, developed from different points of view. Next, the concepts, procedures and application issues of sensory evaluation are presented. Different aspects on study of human body shape, including its historic background, physical study and psychological or aesthetic study are presented. Based on the results of the historic study, we propose three experiments, aiming at acquiring perceptual data on human body shapes from design experts and consumers respectively.

Computation tools used for formalization and modeling (Chapter 3)

For formalizing and modeling human perception data, we choose three intelligent techniques, including fuzzy techniques, decision trees and fuzzy cognitive maps. We first introduce the concepts of fuzzy sets, fuzzy relations and the related operations, fuzzy logic, and fuzzy inference, which mainly focuses on the Mamdani method. Next, two algorithms of decision trees, i.e. CART and Fuzzy-ID3 are presented. Finally, the development of a fuzzy cognition map is described with more emphasis on how it is used to present social-cultural relations.

Modeling the relations between body measurements and human perception on human body shape (Chapter 4)

Using the intelligent techniques presented in Chapter 3, we propose several models to characterize different perceptual data sets obtained from the three evaluation experiments described in Chapter 2. These models permit to characterize the relation between the body ratios and sensory descriptors describing body shapes (naked or with garment design), and the relation between these sensory descriptors and the desired fashion theme. From these models, we obtain a set of rules, which will be used in the proposed design support system for evaluating and selecting new designs.

Implementation of the intelligent fashion design support system (Chapter 5)

All the models and rules developed in Chapter 4 are combined together and constitute an integrated system, permitting to automatically generate evaluations of a new garment style for a specific body shape. The results of the evaluations will provide a useful support for suggesting the most appropriate decision about a new design style and its accordance with specific body shapes towards a specific fashion theme. Moreover, in the same system, the differences between various body shapes and between various garment styles can be quantitatively computed and analyzed. For designers, this treatment is significant for understanding relations between body shapes and styles and identifying the most relevant garment design for a specific consumer.

Chapter 1 Fashion Design and Fashion Marketing

In this chapter, we will present the basic concepts of fashion design and fashion marketing. Especially, we will focus on consumer's need of personalization and their decision process for purchasing fashion products. Based on these concepts, we introduce the general scheme of the decision support system which is proposed in this thesis. This system will help fashion designers to develop new personalized fashion products.

1.1 Fashion Design

1.1.1 Definition of Fashion

In simplest terms, fashion is defined as "a popular or the latest style of clothing, hair, decoration, or behaviour" [Oxford Dictionaries Online, 2012]. This concept is frequently used in apparel industry for representing garments and associated products and services. For more extensive definition, fashion is not only a style, but also a complex phenomenon from psychological, sociological, cultural, or commercial points of view [BRANNON, 2005].

As a psychological response, fashion is seemed as an outlet for expressing the self. Clothing simultaneously conceals and reveals the body and the self. In daily life, when people choose a piece of garment, they will first consider colors, texture and other details which fit to their personal tastes. While wearing clothes, they will evaluate whether the corresponding images express their personalities correctly.

As a sociological phenomenon, fashion is used not only to reflect personal style but also to manipulate the public image in order to meet situations and expectation of others. The engine of fashion is sparked by following the leader and being distinctive [FLÜGEL, 1930].

As a popular culture, fashion can be considered as an information flow transferred among designers, consumers, marketers and other intermediaries in the whole fashion environment. Although fashion concepts are quite different in various regions, new fashion trends can always be generated and spread by communication between them. They are influenced by each other, like communication of other cultural phenomena.

As a commercial line, fashion has become a global economic entity. Fashion industry has been developed in most major cities. Traditionally the most important five centers of fashion industry in the world are Paris, London, Milan, New York and Tokyo. Last decades emerged and evolved new centers of fashion, whose value may not be global but regionally important. These new centers are mainly located in Holland, Belgium, Island, Denmark, Spain, India, and China [BRUZZI & GIBSON, 2000].

1.1.2 Nature of Fashion Design

Fashion has two important characters, i.e. change and creating. The competitive ethos of fashion industry revolves around seasonality. In order to keep the change intrinsic to the fashion taking place in the market, the industry must continually create new products [EASEY, 2009]. Fashion design is one important stage in the process of new products development [URBAN & HAUSER, 1993].

Fashion design is the art of application of design and aesthetics or natural beauty to clothing and accessories, and furthermore is also the art dedicated to the creation of lifestyle. It is influenced by cultural and social latitudes, and has varied over time and place.

In a fashion design process, fashion designers work in different ways. Some people are used to sketching their ideas on paper, while others drape fabric on a mannequin or real human body. Having been satisfied with the fit of his/her prototype, the designer will deliver it to a professional pattern maker, who will then make the finished patterns manually or using a garment CAD system. The designer's prototype is different from the finished patterns because the former is a stylish design scheme while the latter includes all technical parameters and constraints for garment production. In most of cases, fashion designers only have fashion concepts and do not consider technical aspects of garment realization. Their work is more conceptual, abstract, and imaginary. However, the pattern maker's job is very precise and painstaking. The fit of the finished garment depends on their accuracy. The finished prototype is made up and tried on a model to evaluate whether its illustration express the conception correctly [SORGER & UDALE, 2006], [JONES, 2005].

Although a fashion design process can be quite different from another, some common qualifications are required to all fashion designers. They must consider who is likely to wear the designed garment and the wearing situations. It is essential to understand what is being offered and therefore to appreciate the customer’s perception on products. They should also have working experience with a wide range of materials, colors, patterns and styles, and capacity of mastering their combinations for new creations.

1.2 Fashion Marketing

Fashion market is different from a classical market. In fact, until early in the twentieth century it was almost solely the domain of kings, queens, aristocrats and other important people. However, with great changes in the modern society, mainly due to technology and increasing globalization, fashion marketplace is now open to everyone. As fashion is a both reflective and creative field, it is necessary for fashion marketers to be aware of the factors surrounding the market and develop a broad understanding of the issues that can affect the garments that can be seen in any high street store [EASEY, 2009].

Fashion market can be generally segmented into three main categories according to the cost of development and the scale of production. They are haute couture, designer wear and Street fashion, shown in figure 1-1.

Figure 1-1: Decomposition of Fashion Market

Haute couture offers a couture garment that is made to order for an individual customer and usually made from high-quality and expensive fabrics, sewn with extreme attention to details and finished by using time-consuming and hand-executed techniques. Look and fit take priority over the cost of materials and the time it takes to make. Until the 1950s, fashion clothing was predominately designed and manufactured on a made-to-measure or “haute couture” basis (high-fashion in French), with each garment being created for a specific customer. Nowadays, haute couture houses are still the major fashion leaders of the world and they are run by internationally recognized designers. Designers show their collections at least twice a year and sell individual garments with extremely high cost. For most of designers, the catwalk shows are essential events for displaying their new designs to public [EASEY, 2009].

Designer wear is also called ready-to-wear. It permits to keep strict quality control but much less expensive than haute couture. In this context, designers wish to offer their stylish and high quality designs to a wider audience. Ready-to-wear is actually located between haute couture and street fashion. Compared with products in a mass market, garments of ready-to-wear are still expensive because they are usually found in designers’ shops, independent stores and some exclusive department stores. Designs are not uniquely produced but still in limited quantities.

Ready-to-wear collections are usually presented by fashion houses every season in special occasions like Fashion Week. It takes place on a city-wide basis and occurs twice a year [EASEY, 2009], [BRUZZI & GIBSON, 2000].

Street fashion, also called mass market, is a market in which most people buy their clothes. Currently Fashion Industry relies more on mass market sales. Mass market caters for a wide range of customers, and produces ready-to-wear clothes in large quantities and standard sizes. Cheap materials, creatively used, produce affordable fashion. This market is undergoing many changes [EASEY, 2009].

Marketing is defined as "an organizational function and a set of processes for creating, communicating, and delivering values to customers and for managing customer relationships in ways that benefit the organization and its stakeholders" [AMERICAN MARKETING ASSOCIATION, 2011]. It generates a strategy that underlies sales techniques, business communication, and business developments. It is an integrated process through which companies build strong customer relationships and create values for their customers and for themselves [KOTLET & AMSTRONG, 2010].

Market research is used to refer to research into a specific market, investigating such aspects as market size, market trends, competitor analysis, and so on. Differently, marketing research is a much broader concept, covering investigation into all aspects of the marketing of goods or services, such as product research and development, pricing research, advertising research, distribution research, as well as all the aspects of market analysis covered by market research [EASEY, 2009].

Fashion marketing is the application of a range of techniques and a business philosophy, centered upon the customer and potential customer of clothing and related products and services in order to meet the long-term goals of the organization [EASEY, 2009]. The very nature of fashion, where change is intrinsic, gives different emphasis to marketing activities. Furthermore, the role of design in both leading and reflecting consumer demand results in a variety of approaches to fashion marketing. While marketing can help to provide the knowledge and skills needed to ensure that the creative component is used to best advantage, allowing businesses to succeed and grow.

In practice, there are enormous variations in the size and structure of businesses serving the needs of customers in fashion industry. From a small business comprising a self-employed knitwear designer to major multinational corporations such as Liz Claiborne or Zara, diversity remains a key feature. With legislative changes and expansion of EU, progressive removal of trade barriers on a global scale and development of Internet, fashion industry is increasingly a global business [TUNGATE, 2005]. This implies considerable variations in a cultural, social and economic perspective of participants. The consequence of these variations in size, experience and perspective is that the practice of fashion marketing is not uniform at national level, let alone at international level.

1.3 Relation of Fashion Design and Marketing

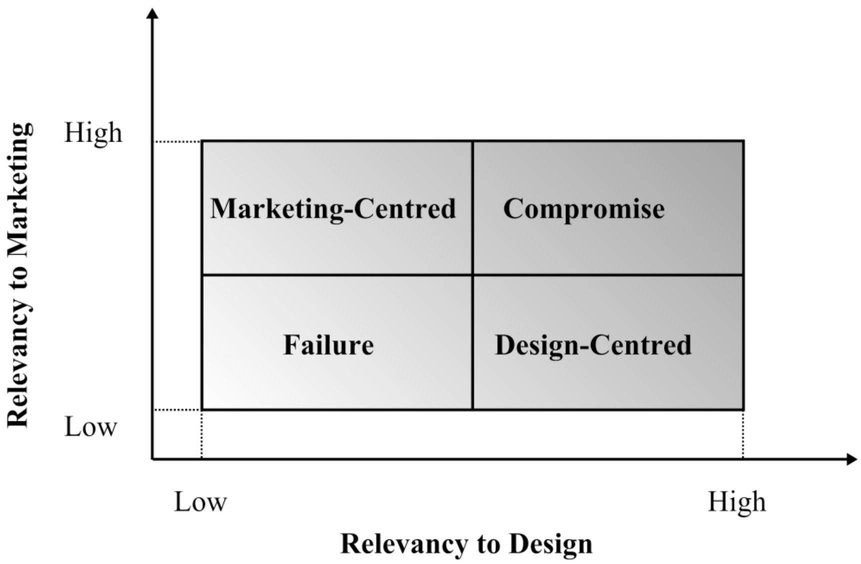


Figure 1-2: Segmentation of the Relation between Marketing and Design

With respect to new product development in fashion industry, the relation of fashion design and marketing can be described by the segmentation in figure 1-2, where the vertical axis represents the effects of marketing and the horizontal axis the effects of design. There are four concepts in this relationship: failure, design-centered, marketing-centered and compromise between design and marketing.

Obviously, if a new product is relevant to neither design nor marketing, it can be regards as a failure. In most cases, this is due to the fact that design ability is overestimated and customers' preferences and the need for profit are neglected.

From the design-centered point of view, fashion experts are the real force for creation and their ideas and comments on new fashion products are directly sold to the general public. In practice, design-centered products deal with all marketing activities through either public relations or advertising departments or agencies [EASEY, 2009]. Consumers and potential consumers can be viewed as people to be led or inspired by creative styling that is favorably promoted. At the extreme, it is rationalized that the only people who can appreciate creative styling, in a financial sense, are the more wealthy sections of the society. Research within such a perspective is limited to monitoring the activities of others who are thought to be at the forefront of creative change. But the principal weakness of this approach is that it depends ultimately on the skill and intuition of the designer for consistently meeting genuine consumer needs and consequently earning profit.

From the marketing-centered point of view, the role of marketing is dominant and it asks designers to respond to specifications of consumer requirements, already established by marketing research. Detailed cost constraints are often imposed and sample garments pre-tested by, for example, retail selectors who may subsequently demand changes to meet their precise needs. Several major retail stores still operate systems not too far removed from this, with merchandisers and selectors exerting considerable control over designers. The result, according to many, is a certain blandness in the design content of garments available from such retail outlets. It is argued that marketing constraints have strangled the creative aspects of design. Taking profitability as a measure of popularity, this restrictive prescription for design seems to work for many firms. Whether popular acceptance of fashion designs equates with good design is another matter [EASEY, 2009].

From the point of view of establishing a compromise between design and marketing, it has more advantages than the design-centered and marketing-centered concepts for the following reasons. The business success of the design-centered concept only depends on a good promotion of fashion style. Therefore, this concept is applicable to a very limited number of transactions only involving expensive garments for an elite market. Considering fashion design as a function of marketing research, the marketing-centered concept fails due to the two following facts: 1) many people do not know their preference exactly until products are presented; 2) their preferences will change over time. Under the concept of compromise between design and marketing, a good fashion design should be accepted by both consumers and experts (designers, retailers and marketers). As it has high relevancy in both aspects, this concept will lead to the highest profit. This concept attempts to embrace the positive aspects of high concern for design, customers and profit by recognizing the interdependence of marketing and design. If designers understand how marketing can enhance the creation process and marketing personnel masters how fashion design can lead to an appropriate response to customer requirements, great business progresses can be made. In this context, perceptions from consumers and experts are both important for the process of new product development.

1.4 Mass Customization

Fashion industry is undergoing rapid evolutionary changes that have resulted from the digital revolution, globalization, and consumer demands. As a general business trend, consumers desire to personalize the style, fit and color of the clothes they choose in order to show his/her original personality [Lim, 2009]. Given the changing characteristics of consumer personalized order, the current mass production systems cannot satisfy both consumers and manufacturers. One resource that fulfils the needs for personalization and a low-cost customized product is mass customization [WILSON & ROSEN, 2005].

Mass customization is a popular trend of retail method in fashion market these two decades years, which is general defined as "developing, producing, marketing and delivering affordable goods, and services with enough variety and customization that nearly everyone finds exactly what they want " [PINE, 1993]. Mass customization aims at producing goods and services catering to individual customers' needs with near mass production efficiency [TSENG & JIAO, 2001].

As a business paradigm, mass customization provides an attractive business proposition to add value by directly addressing customer needs and in the mean time utilizing resources efficiently without incurring excessive cost. This is particularly significant at a time where competition is no longer based on just price but conformance of dimensional quality. Today, customization has been widely accepted in several key industries such as agriculture harvesting machines, trucks, commercial airplanes, elevators, computer hardware, buildings and others [PILLER & TSENG, 2010]. Mass customization is a process for implementing personalization. In some respects, personalization is a goal and mass customization is the way to accomplish that goal [PILLER & TSENG, 2010].

The concept of mass customization in fashion industry is to design and produce new various fashion products with short life cycles and low costs meeting personalized requirements of consumers at the level of comfort and fashion style. According to this concept, the key varieties are personalization, fit and design [IVES & PICCOLI, 2003]. Furthermore, the trends of advanced mass customization are more quick, economic and professional.

The general procedure of mass customization in fashion industry is to firstly obtain customer measurements by a computer technology by a sale man with the aid of a computer, secondly enter the data into a computer and alter specifications as preferred by the customer, finally send adjusted measurements to fabric cutting machine to obtain customized garment pieces [BURNS &BRYANT, 1997]. Some high techniques are used in current advanced mass customization of fashion industry. They are mainly describes as two aspects, 3D body scanning technology and 3D virtual try-on technology [LIM, 2009].

3D body scanning technology is nowadays developed all over the world for fashion mass customization. Shown in the Figure 1-3, the typical 3D body scanning system is established by Assyst Company from UK. The similar systems are also created by the famous French company, Lectra, and other advanced CAD companies in the world. The 3D body scanners capture the outside surface of the human body using optical techniques in combination with light sensitive devices. The laser and light-based systems are the primary types of body scanning systems. For mass customization, the individual measurements and image taken from the 3D body scan can be automatically transferred into a computer database and an intermediate software program can suitably utilize the information for mass customization or virtual try-on technology [KEISER & GARNER, 2003]. The 3D body scanning technology succeeds to acquire accurate human body size data, save the cost of production and enhance the profit in the fashion product life cycle [FAN et al., 2004].

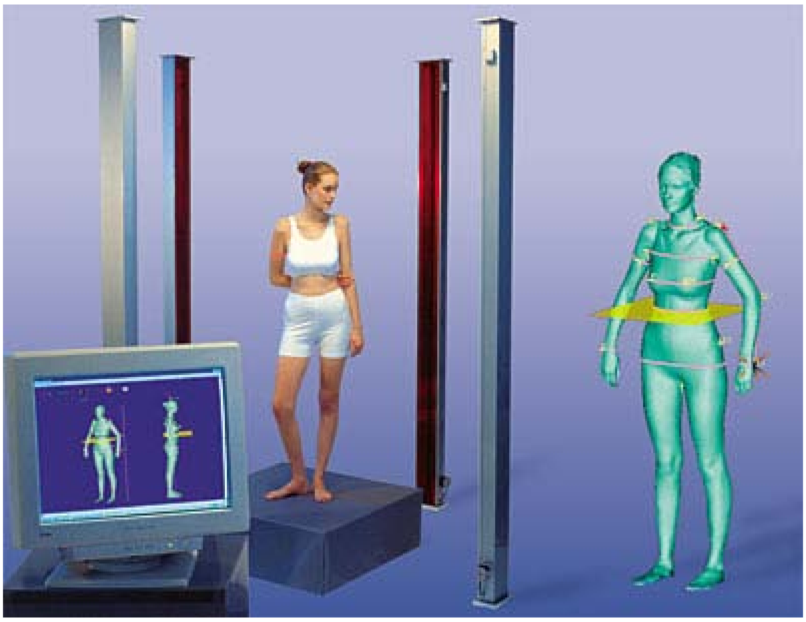


Figure 1-3: Assyst Human Solution 3D Body Scanner

(Source: http://www.assystbullmer.co.uk)

3D virtual try-on technology is mainly used in two fields. One is the support of 3D virtual design and another is the support of 3D virtual personalized service for online apparel retailing.

Several garment CAD systems including Browzwear, Optitex, Lectra, and others have developed software for apparel industry enabling visualization of garments on 3D avatars [VIRTUAL FASHION TECHNOLOGY, 2007]. These avatars can be adjusted to generally mimic a specific set of fit measurements by fine-tuning points of measure, such as bust, waist, hip, abdomen, etc. Virtual garment patterns can be set to sew together on a virtual avatar demonstrating the potential fit of the garment [ISTOOK, 2008]. Figure 1-4 presents the 3D fashion product engineering software, Modaris 3D, which is a powerful and user-friendly solution for flat pattern making, grading, and 3D virtual prototyping in order to meet industry demands for shorter lead times, better fit, and streamlined silhouette development.

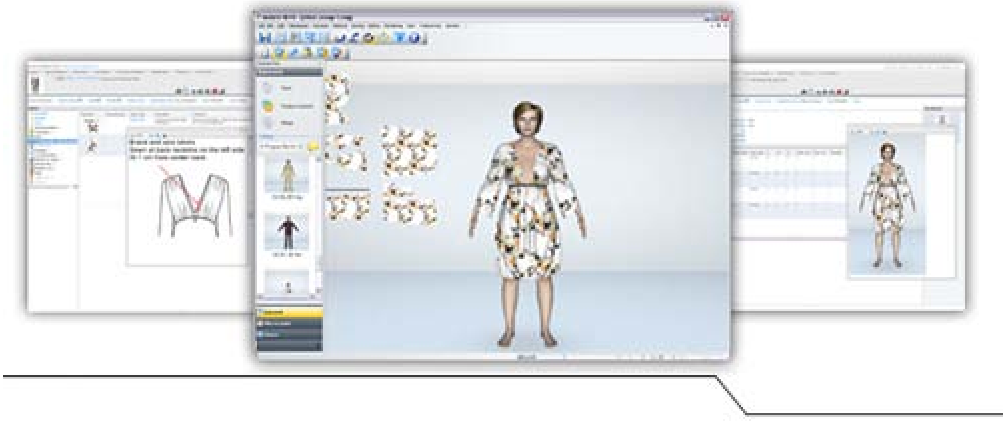


Figure 1-4: Lectra Modaris 3D Software

(Source: http://www.lectra.com)

The 3D virtual try-on personalized service has been offered experimentally on some websites of fashion retailers, such as Sears, H&M, Adidas, Speedo, Levi Strauss and so on [LIM, 2009]. Although virtual try-on technologies allow consumers to evaluate clothing fit on Internet, it is not yet widely available and the technologies should be further developed to include the use of 3D virtual avatars and garments. Also, creating virtual clothing that drapes and moves on the body like real fabric has been still difficult [LIM, 2009]. The online 3D virtual try-on personalized service in figure 1-5 is developed by Optitex. This system can not only provide the simulation of the clothes selected on personalized 3D virtual avatar, but also present the recommendation of matching in the right side.

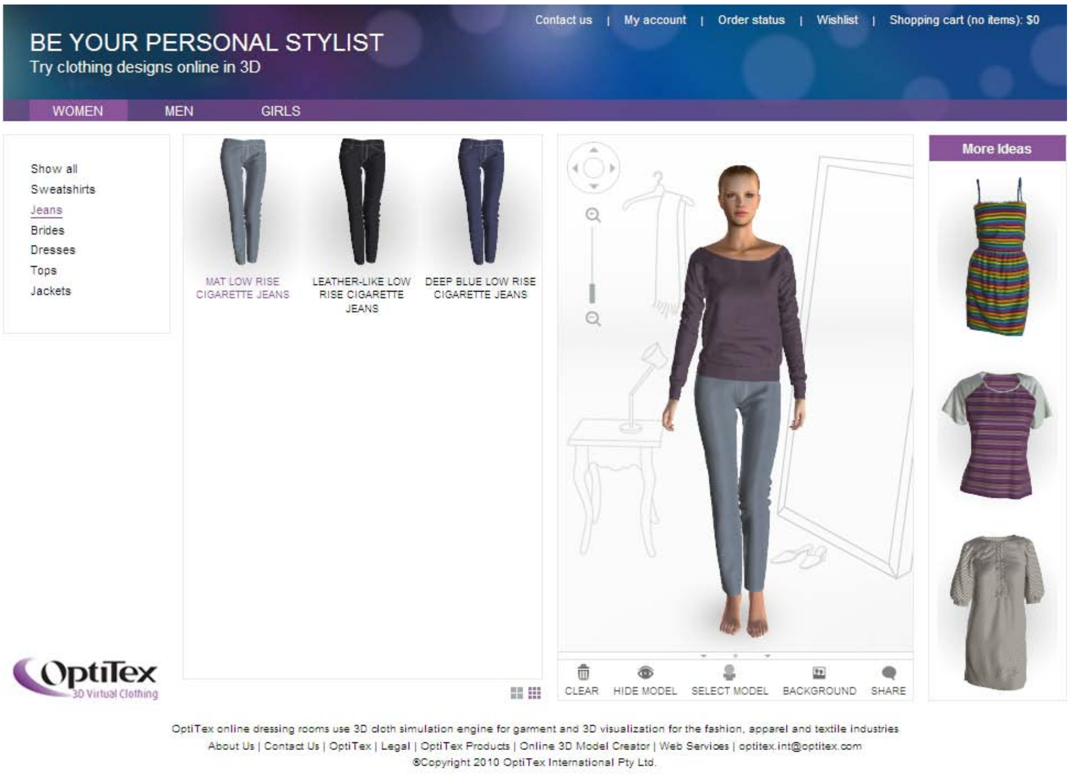


Figure 1-5: Online 3D Virtual Try-on Personalized Service Supported by Optitex

(Source: www.optitex.com)

1.5 Fashion Decision Support System

In practice, trained fashion professionals should play an important role in garment mass customization in order to recommend or create personalized fashion designs. It is hoped that professionals can help customers to choose suitable styles as specifically as possible for each design process. Also, a personalized design process needs to integrate fashion expert's knowledge, experience and perception so that the corresponding CAD system adjusts styles and sizes of patterns adapted to each specific body shape. In practice, if a designer working for a mass market is more familiar with both the consumer's and expert's perceptions around the new design, the new product development process will become more efficient and economic.

For the purpose of improving the current garment mass customization process by compromising fashion design and marketing, our study will focus on development of a fashion decision support system based on the perceptions of consumers and fashion experts. This systems aims at evaluating a set of design styles in order to select the most suitable one, meeting customer's personalized preferences, needs and restrictions. We hope that this system will be integrated into a current garment CAD system in order to support designers to judge their new creations. It will be particularly significant for realizing mass customized retailing in apparel industry.

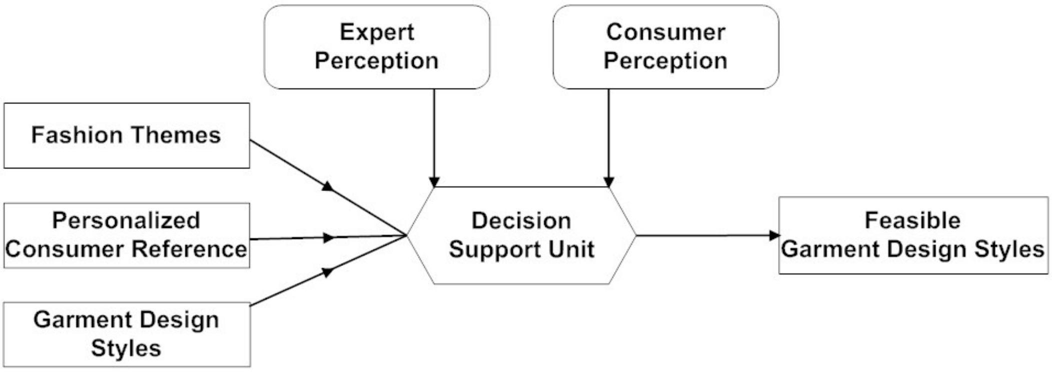


Figure 1-6: Fashion Design Support System for Garment Mass Customization

The structure of our fashion support system is presented in Figure 1-6. Its key components and important issues are described as follows.

(1) Fashion Themes

In practice, the forecast of fashion trends and fashion market permits to form several fashion themes for each new season [BRANNON, 2005]. Fashion designers can select popular fashion themes for their creation work.

(2) Personalized Consumer Reference:

For fashion products, the personalized reference of a consumer includes the physical measurements of his/her specific body shape, color of skin, age, season, dressing occasions and environment, and so on.

(3) Garment Design Styles:

Briefly, a garment design should be submitted to a target fashion market. According to the fashion themes in trend, fashion designers can select classical styles or create new ones for new product development.

(4) Expert Perception:

In our system, the expert perception is involved in the evaluation of basic and concrete sensory descriptors describing the basic nature of male body shapes (naked bodies and dressed bodies) to be evaluated [BRANGIER & BARCENILLA, 2003]. A regular sensory evaluation procedure is adopted to perform this task.

Sensory descriptors are more concrete and more related to the basic nature of body shapes, independent of socio-cultural context of wearers [ZHU, 2010]. From these concrete parameters, design of garment becomes easier. Moreover, these sensory descriptors, such as "bulgy-slim", "swollen-dented" and "forceful-atrophic" are provided by fashion experts, because they are more sensible to evaluate a body shape by using their professional experience.

(5) Consumer Perception:

Unlike the expert perception, the consumer perception is involved in the evaluation of the relationship between fashion themes such as "sporty", "nature" and "attractive" and the previously determined sensory descriptors. These fashion themes are abstract and complex concepts, strongly related to the socio-cultural context of the description on male body shape [BRANGIER & BARCENILLA, 2003]. They represent the general ambiance to consumers provided by the garment or human body shape. In fact, this consumer perception procedure can be considered as a cognition procedure, i.e. the last stage of perception. It is obtained from evaluators' common knowledge and not related to specific human bodies.

(6) Decision Support Unit:

The core component of the proposed fashion support system is the decision support unit, composed of several intelligent models based on the learning data obtained from expert perception and consumer perception. It permits to select the feasible design styles from a list of design styles created according to the personalized reference.

(7) Feasible Garment Design Styles:

They are the garment design styles selected by the decision support unit according to the personalized reference. They take into account a compromise between expert perception and consumer perception. The feasible garment design styles constitute the output of the proposed fashion support system so that the corresponding designer can select the best one as the final decision according to his/her professional experience and competences.

(8) Compromise between fashion experts and consumers:

Both the fashion expert's perception and consumer's perception are important for fashion mass customization. A suitable compromise between them is necessary. This compromise in fashion design will directly lead to a classification of the relations between market acceptance and professional view of design.

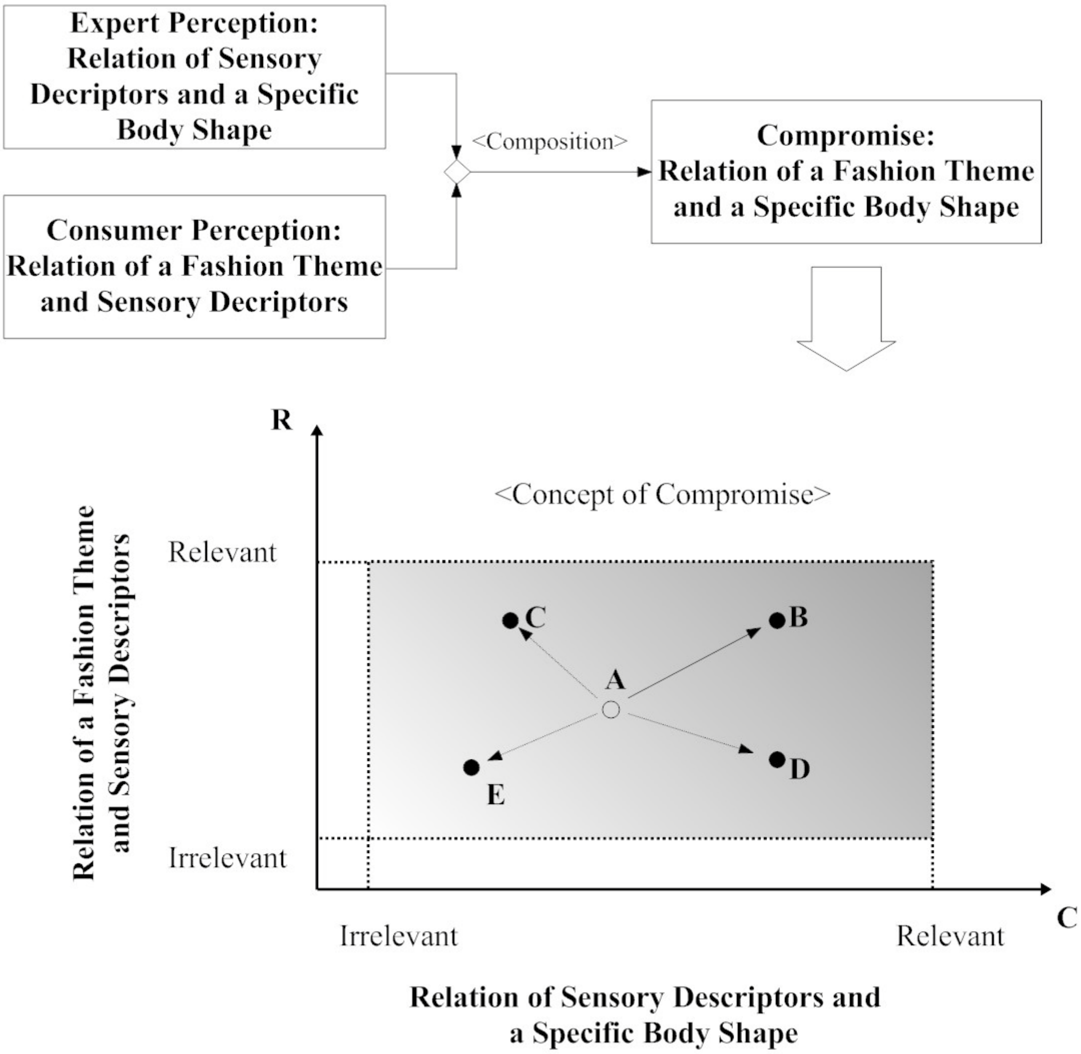


Figure 1-7: Concept of compromise between expert and consumer for a specific fashion theme

Showed in figure 1-7, the concept of compromise for the perception between expert and consumer is expressed by a two-dimensional plan. The horizontal axis C represents the relation between sensory descriptors and a specific body shape (naked or dressed body) evaluated by experts. The value of axis C is the relevancy degree of the specific body shape towards the whole set of the sensory descriptors. The vertical axis R represents the relation between a given fashion theme and the same sensory descriptors. The value of axis R expresses the relevancy degree of the sensory descriptors to the specific fashion theme. One point or a set of points in the R-C plan represents the relation between the specific body shape and the given fashion theme.

(9) Decision process:

The decision permitting to determine whether a new garment style is feasible or not, can be observed from the variation of points on the R-C plan.

For a specific garment style, if the change from a naked (hollow point) to a dressed body shape (black point) on the R-C plan is in the direction of relevancy for both consumer perception and fashion expert perception (from A to B), this garment style will be considered as a feasible style. In this case, we set up a compromise between consumer and expert perception on the new design.

For the other possibilities, if a garment design style permits to change from A to C, this new design is relevant for consumers but not appreciated by experts. If it permits to change from A to D, it is relevant for experts but not appreciated by consumers. If it permits to change from A to E, it is irrelevant for both experts and consumers. In these three cases, the corresponding styles are not feasible designs.

The previous idea constitutes the basic principle of the proposed fashion decision support system.

Our thesis focuses on the realization of several functions of the proposed fashion support system. For simplicity, fashion styles involved in this thesis are limited to the products of man's overcoat. Also, in the concerned experiments, the garment design styles are studied by shapes (including silhouette and lines), without effects of other fashion design elements like colors and material texture. Moreover, the consumer reference is restricted to male body shapes, described by body ratios calculated from physical body measurements. All concerned perceptual elements, including the fashion themes and sensory descriptors, will be treated in the frame of the relations between man's body shape and overcoat design style.

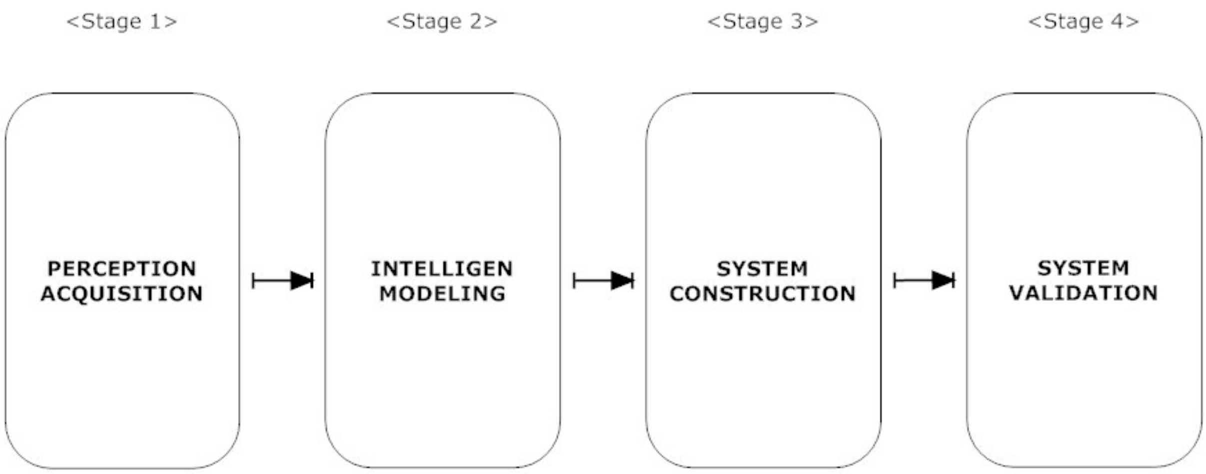


Figure 1-8: Plan of Thesis

As shown in the figure 1-8, my research project is composed of four stages. The first one is the perception data acquisition from both consumers and fashion experts on the relations between man's body shapes and overcoat styles. The second one deals with modeling. In this stage, we will extract the relations from acquired human perception data by using intelligent techniques and transform these relations into the corresponding mathematical models. In the third stage, the previous models will be combined in order to design a prototype. In the final stage, our prototype will be applied by using real data from fashion industry in order to estimate its function.

Chapter 2 Human Perception Acquisition

In this chapter, the contexts and features of human perception, including fashion expert perception and consumer perception, will be described in details. Next, three experiments for acquiring the corresponding perception data are presented respectively. Two of them are based on the method of classical sensory evaluation for collecting fashion expert's perception on body shapes. Another one aims at collecting consumer perception on the relationship between predefined fashion themes and sensory descriptors describing body shapes.

2.1 Human Perception

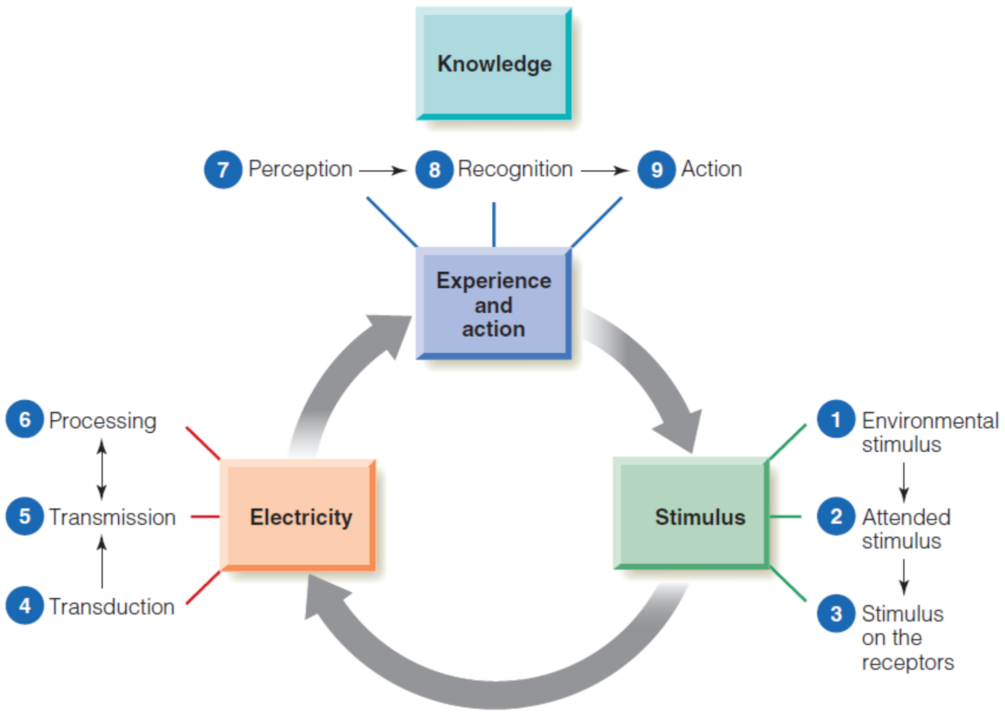


Figure 2-1: Circle of Perceptual Process [GOLDSTEIN, 2010]

Shown in Figure 2-1, the perceptual process can be considered as a sequence of steps that work together to determine our experience and reaction to stimuli in the environment. The whole process is divided into four categories: Stimulus, Electricity, Experience and Action, and Knowledge.

Stimulus refers to what is out there in the environment, what persons actually pay attention to (from Step 1 to Step 2), and what stimulates the receptors (from Step 2 to Step 3). Electricity refers to the electrical signals that are created by the receptors (Step 4) and transmitted to the brain (Step5 and Step 6). Experience and Action refers to our goal—to perceive (Step 7), recognize (Step 8), and react (Step 9) to the stimuli in turn. These three categories form the circle of information flow in perceptual process, and furthermore, the information is dynamic and continually transformed step by step. However, knowledge refers to knowledge persons bring to the perceptual situation, which is located above the other three categories because it can have its effect at many different steps in the whole process [GOLDSTEIN, 2010].

As one step in the circle, perception is regarded as a procedure to transform sensory data into cognition. Perception is the interpretation of what persons feel from external world, and it is quite different from sensation [SOLSO et al., 2005].

In many studies of cognition, human sensation and perception are regarded as the two aspects of how we experience the world. Sensation includes the procedures, receiving, translating, and transmitting raw sensory data from the external and internal environments to the brain. Different from sensation, perception includes the "higher level" procedures, selecting, organizing, and interpreting sensory data into useful mental representations of the world [CARPENTER & HUFFMAN, 2007].

In the procedures of human perception, selection is the first stage permitting to extract the important information. Next, raw sensory data are assembled in a meaningful way before they are useful. So, sensory data is organized in terms of form, constancy, depth, and color. In the final stage, interpretation, the brain uses this information to explain and make judgments about the external world [CARPENTER & HUFFMAN, 2007].

In our daily life, human perception on any physical object is often evaluated by a set of descriptive keywords. These keywords can be organized at two levels [BRANGIER & BARCENILLA, 2003], [ZHU, 2010]:

1) Basic and concrete sensory descriptors, which only describe the basic nature of the object to be evaluated and are independent of its socio-cultural background;
2) Abstract and complex concepts, which are strongly related to the socio-cultural background of the object.

In the proposed fashion support system, a classical sensory evaluation procedure has been adopted for acquiring data from a number of fashion experts for evaluating a set of various male naked bodies and the corresponding bodies with garment design style (Level 1 of perception description). A set of normalized sensory descriptors are generated in the evaluation procedure. Moreover, another procedure evaluating the relations between the fashion themes and the normalized sensory descriptors has been carried out by consumers. This evaluation is strongly related the socio-cultural cognition towards male body shapes (Level 2 of perception description).

2.2 Sensory Evaluation

Sensory evaluation is an important method to acquire sensory data from human perception on a physics object. Generally, it is defined as "a scientific discipline used to evoke, measure, analyze and interpret reactions to those characteristics of foods and materials as they are perceived by the senses of sight, smell, taste, touch and hearing" [STONE & SIDEL, 2004].

As this definition implies, sensory evaluation generally involves the measurement of the sensory properties of foods and other materials in early years. Nowadays, sensory evaluation has become an exciting, dynamic, constantly evolving discipline that is now recognized as a scientific field in its own right [KEMP et al., 2009]. It is used in a boarder context all over the world [STONE & SIDEL, 2004].

Sensory evaluation can be divided by two categories of testing: objective test and subjective test. Objective test provides objective data on the sensory properties of products and are carried out by trained assessors. Subjective test provides subjective data on acceptability, liking or preference, and are carried out by untrained assessors [STONE & SIDEL, 2004].

In this thesis, we choose the discrimination test of the objective tests to acquire the expert perception on male body shapes. The discrimination test is aimed to determine whether there are sensory differences between samples. Basically, the three most used discrimination tests are paired-comparison, duo–trio, and triangle. Other tests have also been developed. However, no more than a cursory examination can be justified due to the lack of application in product evaluation [STONE & SIDEL, 2004]. Paired-comparison is applied in our experiments, as it is relatively easy to be organized and implemented.

2.3 Human Body Shape

2.3.1 Physical Measurements

In general, human body shape is regarded as the cumulative product of skeletal structure and the quantity and distribution of muscle and fat on the body. In fashion industry, human body shapes are generally studied in two aspects, i.e. physical measurements and psychological or aesthetic study.

In physical study of human body shapes, anthropometrics is often used for measurement of human body. It includes numerical data concerning size, shape and other physical characteristics of human beings and could be applied in the fashion design context [KUNICK, 1984], [PHEASANT, 1986].

Furthermore, human body measurement is a key work of anthropometrics, based on landmarks which are located by anatomical points and grouped according to their positions on the body [FAN et al., 2004]. The classic terminologies and methods of body measurement for the clothing field were first published by the Joint Clothing Council [KEMSLEY, 1957]. A standard reference for body measurements was later made available [LOHMAN et al., 1998].

Body measurements were divided into four groups: stature, segment length, body breadth and circumference. In 1996, Beazley suggested a procedure for undertaking a size survey using ISO 8559:1989, which included a natural sequence of body measurement comprising three types of data: horizontal, vertical and others [BEASLEY, 1997].

The body measurements are applied in fashion industry for sizing system. In the latter part of the eighteenth century, most clothing was custom-made by tailors. Various sizing methods were developed by professional dressmakers and craftsmen. Their techniques for measuring and fitting their clients were unique. In the 1920s, the demand for mass production of garments created the need for a standard sizing system. In the 1930s, mail-order houses became popular. This led to frequent returns of ill-fitting garments. Hence, a large anthropometric survey of 10,042 women was conducted to develop a sizing system for women's apparel [DEVARAJAN et al., 2002]. During the last decade, very extensive data were made available for fitting general clothing as well as military wear and equipment [FAN et al., 2004].

Along with the rapid development of a 3D body scanner, the international communities have already made headway in conducting anthropometric surveys using the state-of-the-art technologies in helping to reduce the time and labor involved in the collection of anthropometric data. The intention is to have accurate and automated 3D body analysis information delivered to the garment industry in a form which is immediately useful. The system measures body size, shape and volume in ways which can be customized for each apparel segment and even allows for the direct creation of garment patterns from 3D data, avoiding the interpretation step of using measurements and shape [FAN et al., 2004]

2.3.2 Psychological or Aesthetic Study

The psychological or aesthetic study of human body shape is generally used for characterizing a personalized body image, considered as internal representation of one's outer appearance [THOMPSON et al., 1999]. In other words, body image is the perception of human body. Research on body image can be traced back to the beginning of the twentieth century, when the association between body image and brain damage was identified by neurologists and neuropsychologists. Subsequently, researchers realized the multidimensional nature of body image, namely that body image is attributed to both conscious and unconscious factors, such as emotions, attitudes, wishes and social relationships. Studies on the self-perception of body appearance began in the 1940s. Between the 1940s and the 1950s, numerical scales were designed to self-rate the perception of body attractiveness and appearance. It was found that a high percentage of women were dissatisfied with their body shapes. From the 1960s, increasing evidences have been found that body image affects eating disorders and mental distress [FAN et al., 2004].

The perception of ideal body shape is changeable from time to time and from culture to culture. From the fifteenth to the seventeenth centuries in western cultures, a fat body shape was considered sexually appealing and fashionable in women. The ideal female body shape was portrayed as plump, big-breasted and maternal. By the nineteenth century, this had shifted to a more voluptuous, corseted figure, idealizing a more hourglass shape. In modern western culture, thinness coupled with somewhat inconsistent large breasts and a more toned, muscular physique has become the ideal of feminine beauty [FAN et al., 2004].

In the past decades, while women tend to desire an ideal body shape more smaller and thinner than their current shape, on average men rate their current shape as almost identical to their ideal shape [ALTABE & THOMPSON, 1993], [LAMB et al., 1993]. However, a later research shown the fact that men demonstrate bimodal responding, with some wanting to be smaller and others wanting to be larger [VARNADO-SULLIVAN et al., 2006]. Furthermore, different from the phenomenon that women’s desire for a very thin body, man may face a dual desire to be both lean and muscular [OEHLHOF et al., 2009].

Few people have perfect body shapes. Most people would like to improve their appearance with appropriate clothing, by camouflaging their less desirable attributes and highlighting the more attractive aspects of their bodies [HORN & GUREL, 1981]. In order to design garments to present the best image of the wearer, it is necessary to understand how the perception of body appearance can be modified through clothing. The appearance of the dressed body is a perception of the viewer (whether of the wearers themselves or others) in a social and climatic context. It involves interaction between body, clothing, the viewer and environment [FAN et al., 2004].

2.4 Data Acquisition

2.4.1 Expert Perception Acquisition

The perception of experts is very important to our fashion design support system. It will be used to generate expert rules of the decision support unit. There are two experiments based on the method of sensory evaluation in expert perception acquisition. They are aimed to obtain the relations between naked visual body shapes and sensory descriptors describing body shapes, and between visual body shapes with a garment style and these sensory descriptors.

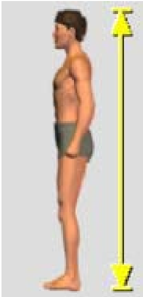
Experiment I: Sensory Evaluation of Naked Visual Male Body Shape

First, a number of various body shapes are selected according to their body measurements. The sensory descriptors are then proposed then validated by trained fashion experts. The components and the procedure of this experiment will be given below.

1) Visual Body Shapes:

The visual body shapes are built on the base of 12 various body types, covering the population of the Eastern regions of China. These 12 body shapes are obtained from the male garment sizing system of the Chinese National Standard GB/T 1335.1-2008 [AQSIQ & SAC, 2008].

As the aim of our project is to design men's overcoats, we select the six key body measurements, considered by fashion experts as the most relevant to the aesthetic effect of men's entire and upper body. These measurements include stature, total length of arm, chest circumstance, neck circumstance, waist circumstance, and hip circumstance. Table 2-1 shows the description of anthropometrics, measuring tools and illustrations for these six measurements.

Item	Description	Illustration
Stature	Standing, legs together, with the head oriented according to the Frankfurt plane. Stature is measured from the top of the head (vertex) to the ground. Manual measurement taking. *Measuring tool used: somatometer*	
Total Length of Arm	The total length of arm is constituted by the length of upper arm and the length of forearm.	
Length of Upper Arm	Standing, length from the upper edge of the shoulder (acromion) to the point of the elbow (olecranon). *Measuring tool used: 3D Scanner*	
Length of Forearm	Standing, measurement of the length from the point of the elbow (olecranon) to the point of the wrist (ulnar styloid). *Measuring tool used: 3D Scanner*	

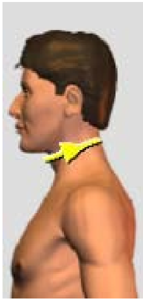
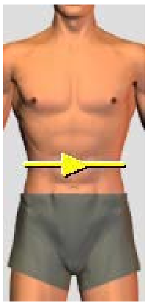
Chest Circumstance	Standing, with indifferent breathing, perimeter taken in a horizontal plane passing at the level of the nipples. *Measuring tool used: 3D Scanner*	
Neck Circumstance	Standing, perimeter taken in a plane passing through the 3rd cervical vertebra and thyroid cartilage. *Measurement tool used: 3D Scanner*	
Waist Circumstance	Standing, with indifferent breathing, perimeter taken in a horizontal plane passing at the level of the line defined by the middle distance between the iliac crests and the lower left and right ribs (floating ribs). *Measurement tool used: 3D Scanner*	
Hip Circumstance	Standing, perimeter taken in a horizontal plane passing in front at the level of the pubis and in back at the level of the most prominent part of the buttock muscle. *Measurement tool used: 3D Scanner*	

Table 2-1: Six Key Measurement Items for Selecting Body Types

Body Type	BM 1	BM 2	BM 3	BM 4	BM 5	BM 6
CY 155	155	51	76	33.4	56	78.8
CY 170	170	55.5	88	36.4	68	88.4
CY185	185	60	100	39.4	80	98
CA 155	155	51	72	32.8	56	75.6
CA 170	170	55.5	84	35.8	68	85.2
CA185	185	60	96	38.8	80	94.8
CB 155	155	51	72	33.2	62	79.6
CB 170	170	55.5	88	37.2	78	90.8
CB185	185	60	108	42.2	98	104.8
CC 155	155	51	76	34.6	70	81.6
CC 170	170	55.5	92	38.6	86	92.8
CC185	185	60	112	43.6	106	106.8

BM 1: **Stature**
BM 2: **Total Length of Arm**
BM 3: **Chest Circumstance**
BM 4: **Neck Circumstance**
BM 5: **Waist Circumstance**
BM 6: **Hip Circumstance**
Unit: **cm**

For the representation of code:

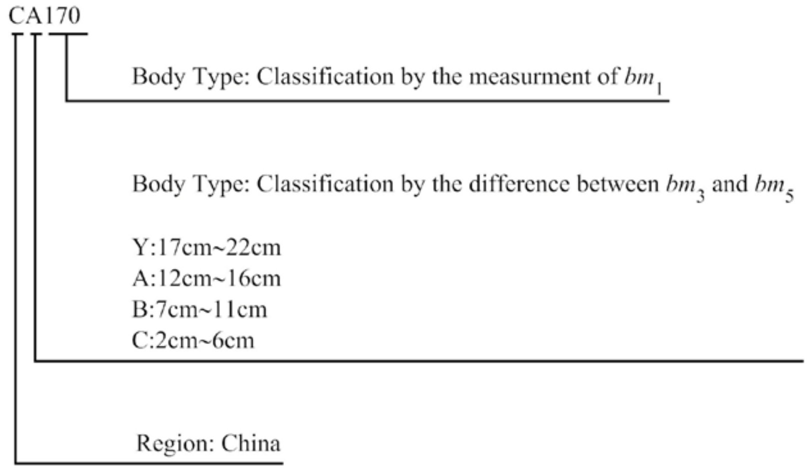


Table 2-2: Twelve Body Types and their Corresponding Measurements

Next, we selected 12 representative body types from the standard GB/T 1335.1-2008, expressed by the following codes: CY155, CY170, CY185, CA155, CA170, CA185, CB155, CB170, CB185, CC155, CC170, CC185 [AQSIQ & SAC, 2008]. The numbers of these codes represent different heights, e.g. CA170 means that the concerned body shape has a height of 170cm. The symbols “CY”, “CA” and “CB” and “CC” represent four frequently used classes of upper body shapes. Furthermore, as CA170 is set to be the standard body type in GB/T 1335.1-2008, we use it as a reference for comparing all body shapes with it. This treatment can make the body shape evaluation procedure easier to understand and lead to more efficient data. The body measurements (BMs) related to these body shapes are listed in Table 2-2.

Figure 2-2: Multiple Angles for Virtual Body Shape of CA170

According to the measurements in Table 2-2, we built a 3D virtual body shape for each body type with same neutral face expression by using Modaris 3D fit, a software developed by LECTRA Company [CICHOCKA et al., 2007]. The six key measurements are used as control parameters to create different virtual body shapes. During the evaluation, each virtual body shape will be viewed from various angles. Figure 2-2 shows the photos of CA170, captured from nine different angles. The aesthetic effects of the body shape can be completely observed.

2) Sensory Descriptors:

During the evaluation procedure, the trained experts should describe the features of the concerned body shapes using a set of normalized keywords, selected from different references [BAEK et al., 2008], [GIBOREAU et al., 2007]. All the evaluators use the same keywords during their evaluations and receive a training session in order to understand the meaning of these descriptors. The method of semantic differential scale is used for expressing these descriptors. It is a widely used technique in sensory evaluation [EASEY, 2009], [STONE & SIDEL, 2004].

In the method of semantic differential scale, a series of bipolar (opposite) adjectives of descriptive phrases are presented to the respondent at opposite ends of a five or seven point scale [EASEY, 2009]. Evaluators are asked to indicate which grade scale best describes their feelings towards the object.

A general example is shown in Figure 2-3. " *Thin - Fat* " is a pair of adjectives used as a semantic differential scale. It has five intensity levels or evaluation scores represented by $\{S_1, S_2, S_3, S_4, S_5\}$, corresponding to the linguistic values {"Very Thin", "Thin", "Neutral", "Fat", "Very Fat"}. We assume that the expert evaluators can not have no answer choice (i.e. unknown is not possible).

Thin	S_1	S_2	S_3	S_4	S_5	**Fat**

Figure 2-3: General Semantic Differential Scale of "*Thin-Fat*"

During the evaluation procedure, the paired-comparison test has been applied. Each evaluator is asked to give a score by comparing a virtual body shape with the standard body shape CA170. This score, varying in a linguistic scale of 9 intensity levels, represents the difference between these two body shapes (see Figure 2-4).

Sensory Descriptor

Thin										**Fat**
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	

Figure 2-4: Scores of Sensory Descriptor

In this scale of 9 intensity levels, C_1, C_2, C_3, C_4, C_5, C_6, C_7, C_8, C_9 correspond to the following predefined linguistic values related to "fat": "*very inferior*", "*inferior*", "*fairly inferior*", "*a little inferior*", "*neutral*", "*a little superior*", "*fairly superior*", "*superior*", "*very superior*". For "*Thin*", the corresponding linguistic values are "*very superior*", "*superior*", "*fairly superior*", "*a little superior*", "*neutral*", "*a little inferior*", "*fairly inferior*", "*inferior*", "*very inferior*". One of these equivalent values is given by an evaluator for describing the difference of a body shape compared with the standard one. For instance, if C_7 is given in this semantic differential scale for body shape CC 155 compared with standard body shape CA 170, we can conclude that CC 155 looks *fairly superior* "*Fat*" related to CA 170 or *fairly inferior* "*Thin*" related to CA170.

In our experiment, 22 pairs of adjectives are selected as sensory descriptors, which are expressed by $(d_1, d_2, \ldots, d_{22})$ in experiment. They come from the physical and emotional keywords frequently used in different references for describing human body shapes. Furthermore, in each pair, the meanings of two poles are opposite. These 22 sensory descriptors are expressed using the semantic differential scale of Figure 2-4 and listed in the Table 2-3.

Sensory Descriptor			
d_1	Thin		Fat
d_2	Slim		Bulgy
d_3	Dented		Swollen
d_4	Atrophic		Forceful
d_5	Short		Tall
d_6	Narrow		Wide
d_7	Flat		Thick
d_8	Non - streamline		Streamline
d_9	Knotty		Smooth
d_{10}	Shrive		Fleshly
d_{11}	Effeminate		Lusty
d_{12}	Fragility		Strong
d_{13}	Inelastic		Elastic
d_{14}	Deft		Awkward
d_{15}	Cabinet		Huge
d_{16}	Unbalanced		Harmonious
d_{17}	Unique		Normal
d_{18}	Unstylish		Stylish
d_{19}	Sebaceous		Muscular
d_{20}	Lazy		Vivid
d_{21}	Light		Heavy
d_{22}	Unsexy		Sexy

Table 2-3: Sensory Descriptors

3) Evaluation Procedure:

During our experiment, three fashion experts are invited to play the role of sensory evaluators. One of them is a professional marketer, mastering a lot of experience on communication with consumers and classification of styles in mass market. The other two ones are specialized in fashion product development, mastering knowledge of both fashion design and fashion marketing.

Figure 2-5: Comparison of CA170 and CC155

In the process of sensory evaluation, the comparison between a specific body shape and a standard one is shown like the example of Figure 2-5. In Figure 2-5, the right body shape CC155 is the object of evaluation and the left one the standard (CA170). In this way, all the twelve body shapes will be presented one-by-one on the right image. They include: “CY155”, “CY170”, “CY185”, “CA155”, “CA170”, “CA185”, “CB155”, “CB170”, “CB185”, “CC155”, “CC170”, “CC185”.

In each comparison between the standard left body shape and a specific right body shape related to a sensory descriptor, one evaluator gives a score or an equivalence value by selecting it from the set $\{C_1, C_2, C_3, C_4, C_5, C_6, C_7, C_8, C_9\}$. When the compared body shapes are both CA170, the equivalence values for all the sensory evaluation are C_5, representing no difference between them.

Finally, the previous equivalence values for each expert descriptor and all the virtual body shapes constitute a (22×12)-dimensional matrix. The example of Table 2-4 represents the perception of one specific expert evaluator on human body shapes.

	CY155	CY170	CY185	CA155	CA170	CA185	CB155	CB170	CB185	CC155	CC170	CC185
d_1	C_5	C_5	C_5	C_3	C_5	C_5	C_6	C_7	C_8	C_7	C_8	C_9
d_2	C_5	C_5	C_5	C_4	C_5	C_5	C_6	C_7	C_8	C_6	C_7	C_9
d_3	C_4	C_5	C_6	C_4	C_5	C_6	C_5	C_7	C_6	C_6	C_7	C_8
d_4	C_5	C_6	C_6	C_3	C_5	C_6	C_3	C_4	C_6	C_2	C_4	C_6
d_5	C_4	C_6	C_7	C_3	C_5	C_6	C_3	C_4	C_6	C_2	C_4	C_6
d_6	C_5	C_5	C_6	C_4	C_5	C_6	C_3	C_5	C_6	C_4	C_6	C_7
d_7	C_6	C_6	C_6	C_5	C_5	C_5	C_6	C_6	C_7	C_6	C_6	C_7
d_8	C_5	C_6	C_5	C_5	C_5	C_5	C_3	C_4	C_4	C_3	C_3	C_2
d_9	C_4	C_5	C_6	C_4	C_5	C_5	C_4	C_5	C_4	C_3	C_4	C_2
d_{10}	C_5	C_6	C_6	C_5	C_5	C_5	C_5	C_6	C_7	C_6	C_7	C_8
d_{11}	C_6	C_6	C_6	C_4	C_5	C_6	C_5	C_6	C_6	C_4	C_6	C_6
d_{12}	C_5	C_6	C_7	C_4	C_5	C_5	C_4	C_6	C_7	C_4	C_5	C_4
d_{13}	C_4	C_5	C_5	C_5	C_5	C_5	C_4	C_4	C_4	C_4	C_3	C_1
d_{14}	C_5	C_5	C_5	C_5	C_5	C_5	C_6	C_6	C_7	C_7	C_7	C_8
d_{15}	C_4	C_5	C_6	C_4	C_5	C_6	C_3	C_6	C_7	C_4	C_6	C_8
d_{16}	C_4	C_6	C_5	C_4	C_5	C_5	C_3	C_4	C_4	C_3	C_4	C_2
d_{17}	C_4	C_5	C_5	C_4	C_5	C_5	C_4	C_5	C_4	C_3	C_4	C_2
d_{18}	C_6	C_6	C_6	C_5	C_5	C_6	C_3	C_4	C_3	C_3	C_3	C_2
d_{19}	C_5	C_6	C_5	C_3	C_5	C_5	C_4	C_4	C_4	C_3	C_4	C_2
d_{20}	C_5	C_5	C_5	C_5	C_5	C_5	C_4	C_5	C_4	C_3	C_3	C_2
d_{21}	C_5	C_6	C_6	C_4	C_5	C_6	C_5	C_6	C_7	C_5	C_7	C_9
d_{22}	C_6	C_6	C_6	C_4	C_5	C_6	C_3	C_4	C_4	C_3	C_3	C_2

Table 2-4: A Specific Result in **Experiment I**

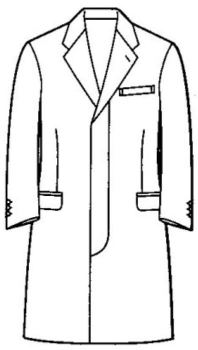
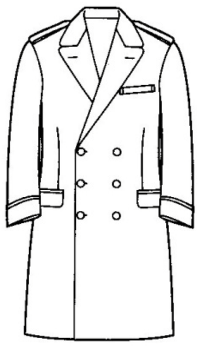
Experiment II: Sensory Evaluation of Virtual Male Body Shape with Design Style

In this experiment, the purpose is to obtain the experts' experience about how fashion styles change the perception of a human body shape. The corresponding components and procedure are described as follows.

(1) Reference Style:

In a design process, fashion designers create a new fashion product using two approaches. One is to change a reference style in order to define a new style. Another is to mix several different reference styles for creating a new one. In the first approach, people view the new style as complete or partial revival of a reference style. In the second approach, a new mixed style is generated under the influence of several different reference styles. In many situations, a new fashion style is created by changing and re-composition of the classical styles as the references [SOGER & UDALE, 2006] [JONES, 2005]

In this experiment, according to the above process of fashion designing, we choose five classical styles of male overcoat as the reference garment styles. Having been prevailed in the history of male fashion, these five styles include: "*Chester*", "*Ulster*", "*Balmacaan*", "*Trench*" and "*Duffle*". Table 2-5 give their corresponding illustrations [GLENVILLE , 2007] [BLACKMAN, 2009].

Style	**Illustration**
Chester	
Ulster	

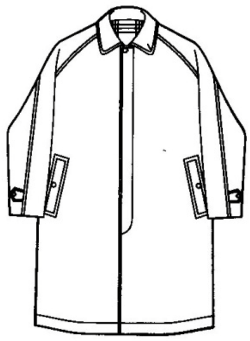
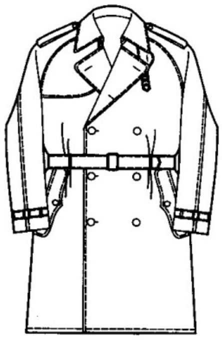
Balmacaan	
Trench	
Duffel	

Table 2-5: Five Reference Styles for Male Overcoat

(2) Evaluation Procedure

In this experiment, the same fashion experts involved in **Experiment I** are invited to perform evaluations with garment styles. Different from **Experiment I** which compares a number of specific naked body shapes shape with a standard one, we ask the evaluators to evaluate how these five styles can influence the standard body shape CA170. This treatment is due to the fact that designers of the mass market usually create styles on a standard mannequin.

The evaluation is carried out with respect to the perceptual difference between the naked standard body shape and the same body shape with a reference style. The used sensory descriptors are the same as those of **Experiment I**.

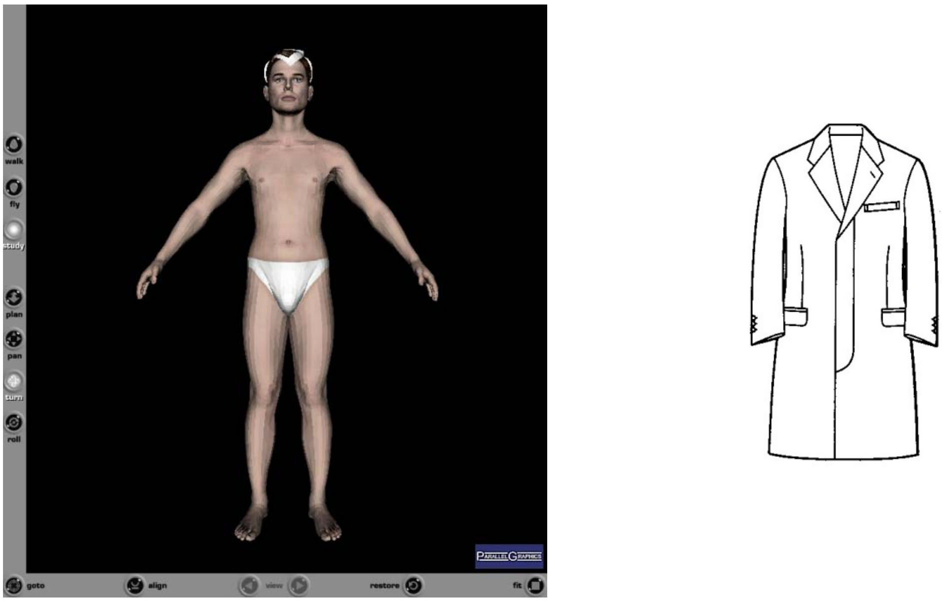


Figure 2-6: The Body Shape CA170 with Garment Style "*Chester*"

Figure 2-6 shows one evaluation scenario for the body shape CA170 with the garment style "*Chester*". The right part is the illustration of "*Chester*" and the left part the virtual naked body shape. Apart from "*Chester*", the other four reference style illustrations are also successively presented at the right part. For simplicity, in this presentation, only garment styles are shown and other key design elements, such as colors and textures, are not taken into account. This treatment can effectively help evaluators to understand more easily the relations between body shapes and garment styles.

In this experiment, for any predefined sensory descriptor, each expert evaluator is also invited to give an equivalence score from the set $\{C_1, C_2, C_3, C_4, C_5, C_6, C_7, C_8, C_9\}$, according to the perceptual difference between the naked body and the body with a garment style. The procedure requires that expert evaluators make their decisions according to their professional experience of fashion design. Evidently, this experiment will lead to more subjective results than **Experiment I**.

Like **Experiment I**, the evaluation results of each expert evaluator also constitute a (22×5)-dimensional matrix. The example of Table 2-6 represents his/her perception on body shapes with garment styles.

		Chester	*Ulster*	*Balmacaan*	*Trench*	*Duffel*
d_1	Thin-Fat	C_4	C_3	C_7	C_6	C_6
d_2	Slim-Bulgy	C_4	C_3	C_8	C_6	C_6
d_3	Dented-Swollen	C_4	C_3	C_7	C_4	C_6
d_4	Atrophic-Forceful	C_8	C_9	C_4	C_7	C_6
d_5	Short-Tall	C_7	C_8	C_4	C_7	C_5
d_6	Narrow-Wide	C_7	C_8	C_5	C_8	C_5
d_7	Flat-Thick	C_6	C_7	C_6	C_7	C_7
d_8	Non-streamline-Streamline	C_9	C_8	C_3	C_6	C_4
d_9	Knotty-Smooth	C_8	C_8	C_4	C_6	C_5
d_{10}	Shrive-Fleshly	C_6	C_5	C_6	C_6	C_7
d_{11}	Effeminate-Lusty	C_7	C_8	C_5	C_8	C_6
d_{12}	Fragility-Strong	C_6	C_7	C_5	C_8	C_7
d_{13}	Inelastic-Elastic	C_5	C_5	C_4	C_6	C_7
d_{14}	Deft-Awkward	C_5	C_4	C_7	C_4	C_7
d_{15}	Cabinet-Huge	C_7	C_8	C_6	C_8	C_6
d_{16}	Unbalanced-Harmonious	C_9	C_9	C_4	C_7	C_8
d_{17}	Unique-Normal	C_7	C_7	C_5	C_4	C_6
d_{18}	Unstylish-Stylish	C_8	C_9	C_3	C_8	C_6
d_{19}	Sebaceous-Muscular	C_7	C_8	C_3	C_7	C_5
d_{20}	Lazy-Vivid	C_6	C_7	C_2	C_8	C_7
d_{21}	Light-Heavy	C_5	C_6	C_7	C_6	C_6
d_{22}	Unsexy-Sexy	C_7	C_8	C_1	C_8	C_7

Table 2-6: A Specific Result in **Experiment II**

2.4.2 Consumer Perception Acquisition

We wish to characterize the social-cultural aspect of human body shapes from consumer perceptions. The cognitive principles about the relations between fashion themes and sensory descriptors describing human body shapes will be extracted from the evaluations of consumers.

Experiment III: Cognition of Fashion Themes and Sensory Descriptors

The components and procedure of this experiment are given below.

1) Fashion Theme:

In general, fashion theme is a central concept for defining a set of design elements. In the important fashion events, fashion themes are often communicated to general public through fashion forecasting reports or seminars [BRANNON, 2005].

Three fashion themes are assumed in this experiment, i.e. “Sporty”, “Nature” and “Attractive”. For each fashion theme, a number of representative photographs, like those of Figure 2-7, are presented in order to make the evaluators understand it more easily.

(a) *Very Relevant* to **Sporty** (b) *Very Relevant* to **Nature** (c) *Very Relevant* to **Attractive**

Figure 2-7: Three Representative Photographs for the Fashion Themes

(Refer to the Publication of Prada Men Autumn/Winter 2009-2010)

2) Degree of Relevancy:

In this experiment, each evaluator or consumer is asked to give a linguistic evaluation score for charactering the degree of relevancy of each sensory descriptor to each fashion theme. The linguistic scores are taken from the set { R_1 = ”*very irrelevant*”, R_2 = ”*fairly irrelevant*”,

R_3= ”*neutral*”, R_4= ”*fairly relevant*”, R_5= ”*very relevant*”}. It is also presented using the method of semantic differential scale shown in Figure 2-8.

Degree of Relevancy of a sensory descriptor to a fashion theme

R_1	R_2	R_3	R_4	R_5
Very Irrelevant	***Fairly Irrelevant***	***Neutral***	***Fairly Relevant***	***Very Relevant***

Figure 2-8: Semantic Differential Scale for the Degree of Relevancy

3) Evaluation procedure:

25 male consumers having various professional backgrounds are invited to take part in this experiment. However, these consumers have many difficulties to understand fashion concepts, fashion themes and sensory descriptors. Therefore, at beginning of the evaluation procedure, we start with a warn-up session, while we train these consumers in an interview by presenting a number of relevant photographs describing the related fashion themes. Also, we give them a complete interpretation on all the involved sensory descriptors.

In the following step, these consumer evaluators fill a predefined questionnaire individually. This questionnaire (see Appendix 1) is based on the method of semantic differential scale in order to obtain the relation between 22 sensory descriptors and 3 fashion themes.

Finally, the results obtained from each consumer evaluator constitute a (22×3)-dimensional linguistic matrix. The example of Table 2-7 represents one consumer’s cognition on the relations between fashion themes and sensory descriptors.

		Sporty	Nature	Attractive
d_1	Thin-Fat	R_3	R_4	R_4
d_2	Slim-Bulgy	R_2	R_4	R_4
d_3	Dented-Swollen	R_2	R_4	R_4
d_4	Atrophic-Forceful	R_5	R_3	R_4
d_5	Short-Tall	R_2	R_3	R_3
d_6	Narrow-Wide	R_4	R_5	R_4
d_7	Flat-Thick	R_3	R_4	R_3
d_8	Non-streamline-Streamline	R_2	R_3	R_3
d_9	Knotty-Smooth	R_1	R_2	R_4
d_{10}	Shrive-Fleshly	R_1	R_3	R_5
d_{11}	Effeminate-Lusty	R_4	R_3	R_4
d_{12}	Fragility-Strong	R_5	R_4	R_1
d_{13}	Inelastic-Elastic	R_4	R_3	R_2
d_{14}	Deft-Awkward	R_2	R_4	R_1
d_{15}	Cabinet-Huge	R_3	R_4	R_4
d_{16}	Unbalanced-Harmonious	R_1	R_1	R_4
d_{17}	Unique-Normal	R_2	R_2	R_4
d_{18}	Unstylish-Stylish	R_2	R_2	R_4
d_{19}	Sebaceous-Muscular	R_1	R_3	R_4
d_{20}	Lazy-Vivid	R_4	R_4	R_2
d_{21}	Light-Heavy	R_2	R_2	R_2
d_{22}	Unsexy-Sexy	R_2	R_1	R_5

Table 2-7: A Specific Result in **Experiment III**

Chapter 3 Computational Tools for Modeling

In this chapter, we will present the computational tools used for modeling different relations in the proposed fashion design support system. These tools, all belonging to the category of artificial intelligence, include fuzzy logic and fuzzy relations, decision tree and fuzzy cognitive map. Now we will start with a brief introduction of the contexts and basic principles of these tools and explain their relevancy to the problems we encounter during our modeling work. The details of the specific applications to the construction of the fashion design support system will be provided in Chapter 4.

3.1 Artificial Intelligence

Artificial intelligence is the art of creating machines that perform functions requiring intelligence when performed by people [KURZWEIL, 1992]. It will permit to realize a series of computations simulating human behaviors of perception, reasoning and decision [WINSTON, 1992].

The foundation of artificial intelligence is involving in multiply disciplines, such as philosophy, mathematics, neuroscience, cognitive psychology, computer engineering, control theory, and linguistics [RUSSELL & NORVIG, 2010].

A great number of computational techniques of artificial intelligence have been developed and successfully applied in different fields. However, in this thesis, we mainly focus on how to model and analyze data obtained from human perceptions and how to model causal knowledge in human cognition using artificial intelligence.

Of the three intelligent techniques involved in my research project, fuzzy techniques play a key role in formalization and analysis of sensory data and human knowledge. Decision trees have been applied for modeling complex relations between sensory descriptors given by experts and basic measurements of human bodies. These models can be considered as empirical models, based on learning data obtained from experiments. Fuzzy cognitive maps have been used for modeling conceptual and causal relations obtained from consumer cognition.

The contexts and methods of fuzzy techniques, decision tree, and fuzzy cognitive map will be described in the following sections.

3.2 Fuzzy Sets Theory

Fuzzy sets appeared for the first time in 1965 in the paper of Lotfi A. Zadeh, entitled "Fuzzy Sets" [ZADEH, 1965]. Since then, theoretical results on fuzzy theory have quickly and massively been developed and applied in different industrial fields.

Especially, Mamdani developed in 1975 a new process control strategy using human knowledge-based fuzzy rules and obtain satisfying control effects on the operation of a steam engine [MAMDANI, 1975]. It can be considered as an empirical model permitting to integrate operator's experience. In 1978, as the first industrial application, the Danish company F.L.Smith performed the control of a cement kiln using a fuzzy model. In Japan, both theoretical research and industrial applications on fuzzy modeling have been quickly developed. Now, the applications of fuzzy techniques are mainly concentrated on domestic appliances like washing machines, air conditioners, cameras and camcorders as well as public devices such as water treatment systems, port cranes, subways and ventilation systems. Compared with other tools of artificial intelligence, fuzzy techniques are particularly efficient for processing information uncertainty and imprecision related to human factors. It is for this reason that researchers have paid much attention to fuzzy techniques when developing decision support systems in uncertain environments, such as finance and medical diagnosis.

3.2.1 Definition of Fuzzy set

In the theory of crisp set (classic set), an element belongs to a set entirely or not. It does not support an element belongs to a set partially. But the concept of fuzzy set is designed to allow the gradations of membership of a set for an element. It is to say that an element is allowed to partially belong to a set.

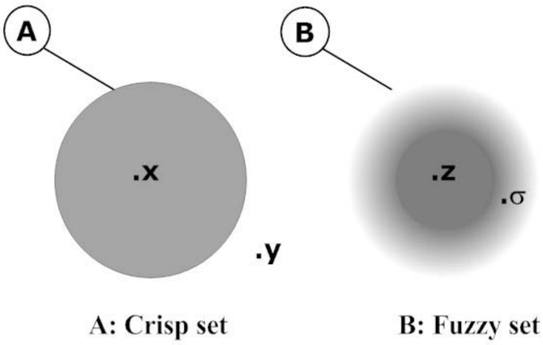


Figure 3-1: Difference between a crisp set and a fuzzy set

In Figure 3-1, the element x belongs entirely to A. The element y does not belong to A. The element z belongs to B totally and the element σ belongs to B partially. The concept of fuzzy set looks like a relaxation of the subset of a universal set. Consequently, fuzzy set is 'vague boundary set' comparing with crisp set [CHEVRIE & GUELY, 1998].

Formally, the membership function μ_A of a crisp set maps all the members of the universal set X to the set {0, 1}.

$$\mu_A: X \rightarrow \{0, 1\}.$$

For a fuzzy set, each element is mapped to [0,1] by its membership function:

$$\mu_A: X \rightarrow [0, 1]$$

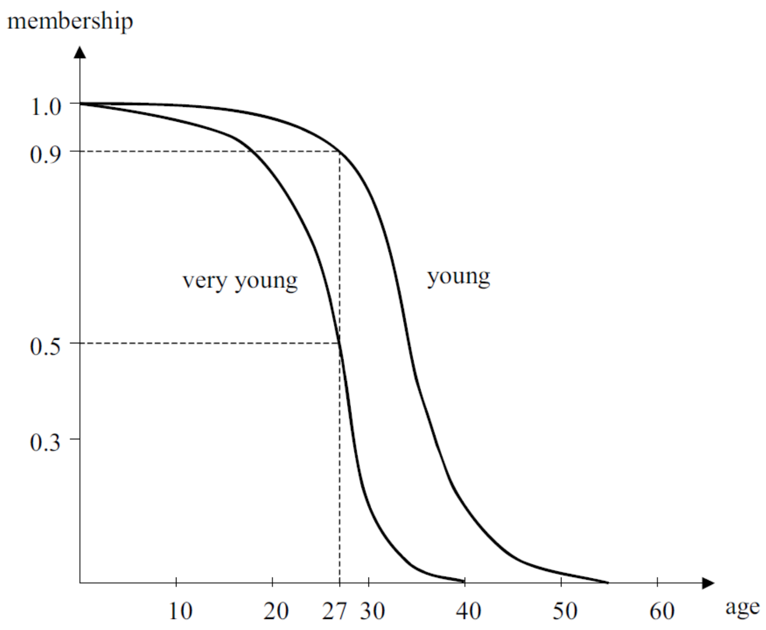


Figure 3-2: Function Membership of Age

We consider the statement "Jenny is young". In fact, the term "young" is vague. In order to represent the meaning of "vague", we define its membership function in Figure 3-2. In this figure, the horizontal axis shows the age and the vertical axis the value of membership function. The curve shows the possibility (value of membership function) of being included in the fuzzy set "young". In this case, the membership degree of "age=10" related to the set of "young" is 1, that of "age=27" is 0.9, and that of "age>60" is 0. The same treating can be applied to other fuzzy sets such as "very young", "middle age", "old", very old". As shown in Figure 3-2, $\mu\_young(27) = 0.9$ and $\mu\_very\ young = 0.5$.

The standard operations of fuzzy sets are given as in follows.

a) We denote the complement set of fuzzy set A as $\bar{A}$. The membership degree of $\bar{A}$ can be calculated as

$$\mu_{\bar{A}}(x) = 1 - \mu_A(x), \forall x \in X$$

b) Membership value of member x in the union takes the greater value of membership between fuzzy sets A and B

$$\mu_{A\cup B}(x) = \text{Max}\,[\mu_A(x), \mu_B(x)], \forall x \in X$$

Of course, A and B are subsets of $A \cup B$.

c) Intersection of fuzzy sets A and B takes smaller value of membership function between A and B

$$\mu_{A\cap B}(x) = \text{Min}\,[\mu_A(x), \mu_B(x)], \forall x \in X$$

Intersection $A \cap B$ is a subset if A or B.

3.2.2 Fuzzy Relation

Fuzzy relations are developed by allowing the relationship between elements of two or more sets to take on an infinite number of degrees of relationship between the extremes of "completely related" and "not related," which are the only degrees of relationship possible in crisp relations. In this sense, fuzzy relations are to crisp relations as fuzzy sets are to crisp sets; crisp sets and relations are more constrained realizations of fuzzy sets and relations [ROSS, 2004].

Fuzzy relations map elements of one universe, say, X, to those of another universe, say, Y, through the Cartesian product of the two universes. However, the "strength" of the relation between ordered pairs of the two universes is not measured with the indicator function (as in the case of crisp relations), but rather with a membership function expressing various "degrees" of strength of the relation on the unit interval [0, 1].

Hence, a fuzzy relation R is a mapping from the Cartesian space X x Y to the interval [0, 1], where the strength of the mapping is expressed by the membership function of the relation for ordered pairs from the two universes, or μ_R(X, Y).

All fuzzy set operations can also be applied to fuzzy relations. For the two fuzzy relations $R \subseteq A \times B$ and $S \subseteq A \times B$, we define the following operations:

(1) Union relation

Union of two relations R and S is defined as,

$$\forall (x, y) \in A \times B$$

$$\begin{aligned}\mu_{R\cup S}(x,y) &= \text{Max}\,[\mu_R(x,y),\mu_S(x,y)]\\ &= \mu_R(x,y)\vee\mu_S(x,y)\end{aligned}$$

In practice, " ∨ " is generally realized using a Max operation. For n relations, we extend it to the following form:

$$\mu_{R_1\cup R_2\cup R_3\cup\ldots\cup R_n}(x,y) = \bigvee_{R_i}\mu_{R_i}(x,y)$$

(2) Intersection relation

The intersection relation $R\cap S$ of two fussy sets A and B is defined by the following membership function.

$$\forall(x,y)\in A\times B$$

$$\begin{aligned}\mu_{R\cap S}(x,y) &= \text{Min}\,[\mu_R(x,y),\mu_S(x,y)]\\ &= \mu_R(x,y)\ \wedge\ \mu_S(x,y)\end{aligned}$$

" ∧ " is usually realized using Min operation. In the same way, the intersection relation for n fuzzy relations is defined by

$$\mu_{R_1\cap R_2\cap R_3\cap\ldots\cap R_n}(x,y) = \bigwedge_{R_i}\mu_{R_i}(x,y)$$

(3) Complement relation

The complement relation $\bar{R}$ of the fuzzy relation R is defined by the following membership function.

$$\forall(x,y)\in A\times B$$

$$\mu_{\bar{R}}(x,y) = 1-\mu_R(x,y)$$

For extension, the composition of two fuzzy relations can be calculated as follows.

Definition: Considering the fuzzy relation R is defined on the universal sets A and B, i.e., $R\subseteq A\times B$ and S on the universal sets B and C, i.e. $S\subseteq B\times C$. The composition $R\circ S$ of two fuzzy relations R and S is expressed by the relation from A to C, which is defined by

$$\mu_{S\circ R}(x,z) = \underset{y}{\text{Max}}\left[\text{Min}\ \left(\mu_R(x,y),\mu_S(y,z)\right)\right]$$

$$= \bigvee_y [\mu_R(x, y) \wedge \mu_S(y, z)]$$

$S \circ R$ from this elaboration is a subset of $A \times C$. That is, $S \circ R \subseteq A \times C$.

If the relation R and S are represented by matrices M_R and M_S, the matrix $M_{S \circ R}$ corresponding to $S \circ R$ can be expressed by.

$$M_{S \cdot R} = M_R \circ M_S$$

3.2.3 Fuzzy Logic

A fuzzy proposition can have its truth value in the interval $[0, 1]$. The fuzzy expression function is a mapping function from $[0, 1]$ to $[0, 1]$.

$$f: [0, 1] \rightarrow [0, 1]$$

In a domain of n dimensions, the fuzzy function becomes:

$$f: [0, 1]^n \rightarrow [0, 1]$$

Therefore we can interpret the fuzzy expression as an n-array relation from n fuzzy sets to $[0, 1]$. In the fuzzy logic, the operations such as negation $(\sim)$, conjunction $(\wedge)$ and disjunction $(\vee)$ are defined in the same way as those of the classical logic.

Definition: Fuzzy logic is a logic represented by the fuzzy expression which satisfies the following conditions:

(1) Truth values, 0 and 1, and variable $x_i \in [0, 1], (i = 1, 2, \dots, n)$ are fuzzy expressions.

(2) If f is a fuzzy expression, $\tilde{f}$ is also a fuzzy expression.

(3) If f and g are fuzzy expressions, $f \wedge g$ and $f \vee g$ are also fuzzy expressions.

The operators in the fuzzy expression are defined as follows for $a, b \in [0,1]$.

(1) Negation $\tilde{a} = 1 - a$

(2) Conjunction $a \wedge b = \mathrm{Min}(a, b)$

(3) Disjunction $a \vee b = \mathrm{Max}(a, b)$

(4) Implication $a \rightarrow b = \mathrm{Min}(1, 1 + b - a)$

3.2.4 IF-THEN Rule

In a fuzzy system, the representation of knowledge is an important issue for inference. When we consider the representation methods of knowledge, the following rule type "if-then" is the most popular form [LEE, 2005].

"If x is a, then y is b."

The rule is interpreted as an "implication" and consists of the "antecedent (if part)" and "consequent (then part)". If a rule is given in the above form and we have a fact in the following form,

"x is a"

then we can infer and obtain new result:

"y is b"

based on the above discussion, we can summarize two types of "reasoning".

(1) Modus ponens

Fact: x is a

Rule: If x is a, then y is b

Result: y is b

(2) Modus tollens

Fact: y is $\bar{b}$

Rule: If x is a then y is b

Result: x is $\bar{a}$

3.2.5 Fuzzy Inference

Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made, or patterns discerned. The process of fuzzy inference involves all of the pieces that are described in the previous sections: Membership Functions, Logical Operations, and If-Then Rules [JIANG & SUN, 1997].

Fuzzy inference systems have been successfully applied in fields such as automatic control, data classification, decision analysis, expert systems, and computer vision. Because of its multidisciplinary nature, fuzzy inference systems are associated with a number of names, such as fuzzy-rule-based systems, fuzzy expert systems, fuzzy modeling, fuzzy associative memory, fuzzy logic controllers, and simply fuzzy systems.

In the proposed fashion design support system, the method of Mamdani is used in the process of fuzzy inference in order to aggregate the expert rules.

The Mamdani's fuzzy inference, frequently used in various applications, was initially built for controlling a steam engine and boiler combination by synthesizing a set of linguistic control rules obtained from experienced human operators [MAMDANI, 1975].

The principle of the Mandani method is often explained through a typical example aiming at characterizing, in a restaurant evaluation procedure, the relation between the quality of service, quality of food and tip. This system is composed of two inputs, one output, and three rules. The basic structure of this system and its parameters are shown in Figure 3-3 [MATHEWORKS, 2011].

The fuzzy inference process is composed of five parts: fuzzification of the input variables, application of the fuzzy operator (AND or OR) in the antecedent, implication from the antecedent to the consequent, aggregation of the consequents across the rules, and defuzzification. The details of these parts are given in the following steps.

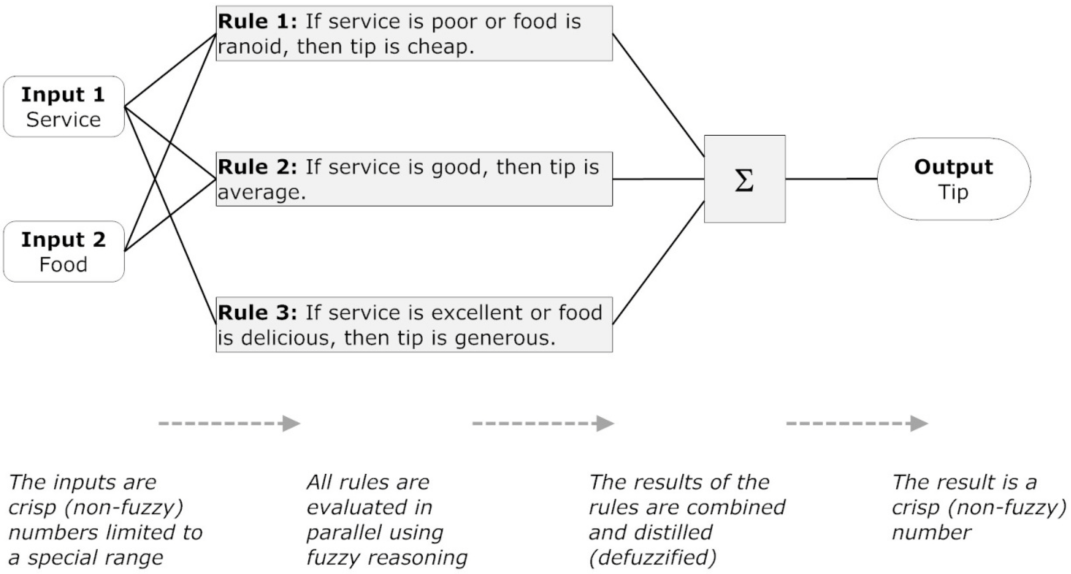


Figure 3-3: Flow of Fuzzy Inference Process

Step 1 of Fuzzy Inference: Fuzzification

The first step is to take the inputs and determine the degree to which they belong to each of the appropriate fuzzy sets via membership functions. The input is always a crisp numerical value limited to the universe of discourse of the input variable and the output a fuzzy degree of membership in the qualifying linguistic set (always the interval between 0 and 1). Fuzzification of the input amounts to either a lookup table or a function evaluation.

In the three fuzzy rules of the previous example, each input should be evaluated using different linguistic values or fuzzy sets: *service is poor*, *service is good*, *food is rancid*, *food is delicious*, and so on. Before the rules are evaluated, the inputs must be fuzzified according to each of these linguistic sets. For example, to what extent is the food really delicious. Figure 3-4 shows how well the food at the hypothetical restaurant (rated on a scale of 0 to 10) qualifies, (via its membership function), as the linguistic variable "*Delicious*". In this case, it rated the food as an 8. while this scale value is corresponding to the graphical definition of *Delicious*, the membership function of *Delicious* is expressed by $\mu = 0.7$.

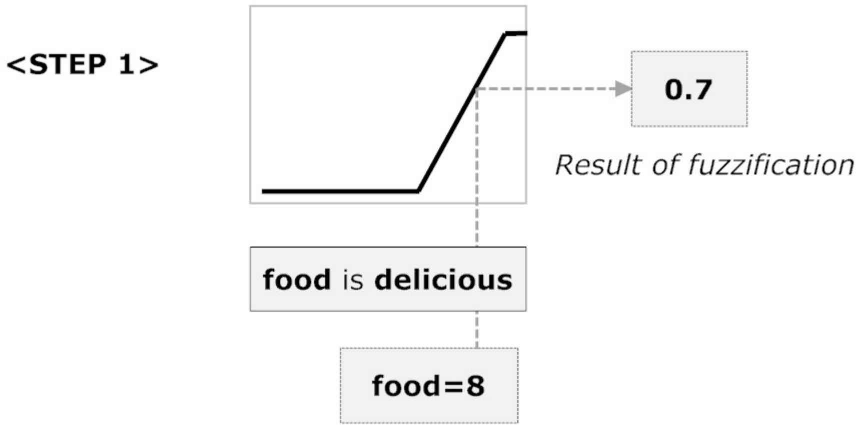


Figure 3-4: Example of Fuzzification

In this manner, each input is fuzzified over all the qualifying membership functions required by the rules.

Step 2 of Fuzzy Inference: Application of Fuzzy Operators

After the inputs are fuzzified, the degree to which each part of the antecedent is satisfied for each rule. The input to the fuzzy operator is two or more membership values from fuzzified input variables. The output is a single truth value.

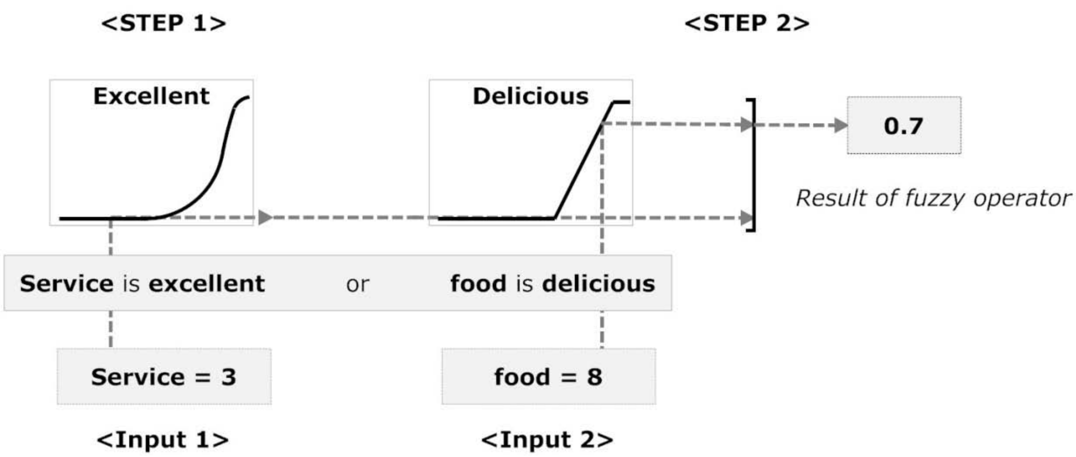


Figure 3-5: Fuzzy Operation

Figure 3-5 shows the OR operator (MAX) at work, evaluating the antecedent of the rule "IF service is excellent or food is delicious, THEN tip is generous." for the tipping calculation. The two different pieces of the antecedent (service is excellent and food is delicious) yielded the fuzzy membership values 0.0 and 0.7 respectively. The fuzzy OR operator simply selects the maximum of the two values, 0.7, and the fuzzy operation for this rule is complete.

Step 3 of Fuzzy Inference: Application of the Implication Method

Before applying the implication method, it must determine the rule's weight. Every rule has a weight (a number between 0 and 1), which is applied to the number given by the antecedent. Generally, this weight is 1 (as it is for this example) and thus has no effect at all on the implication process.

After proper weighting has been assigned to each rule, the implication method is implemented. A consequent is a fuzzy set represented by a membership function, which weights appropriately the linguistic characteristics that are attributed to it.

Shown in Figure 3-6, the consequent is reshaped using a function associated with the antecedent (a single number). The input for the implication process is a single number given by the antecedent, and the output is a fuzzy set. Implication is implemented for each rule. Two built-in methods are supported, and they are the same functions that are used by the AND operator (MIN), which truncates the output fuzzy set, and prod (product), which scales the output fuzzy set.

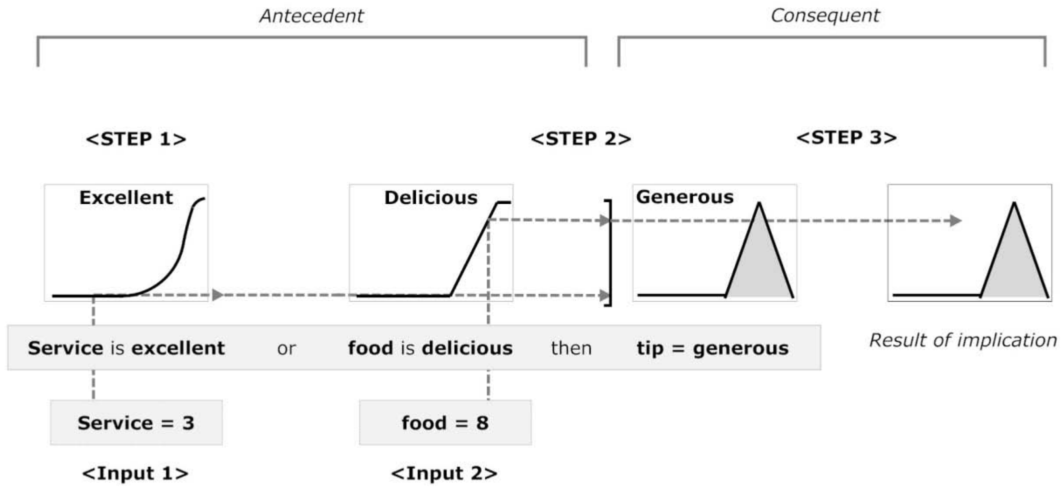


Figure 3-6: Implication of Output in a Rule

Step 4 of Fuzzy Inference: Aggregation of All Outputs

As decisions are based on the testing of all of the rules in a fuzzy inference, the rules must be combined in some manner in order to make a decision. Aggregation is the process by which the fuzzy sets that represent the outputs of each rule are combined into a single fuzzy set. The input of the aggregation process is the list of truncated output functions returned by the implication process for each rule. The output of the aggregation process is one fuzzy set for each output variable.

In Figure 3-7, all three rules in this example have been placed together to show how the output of each rule is combined, or aggregated, into a single fuzzy set whose membership function assigns a weighting for every output (tip) value.

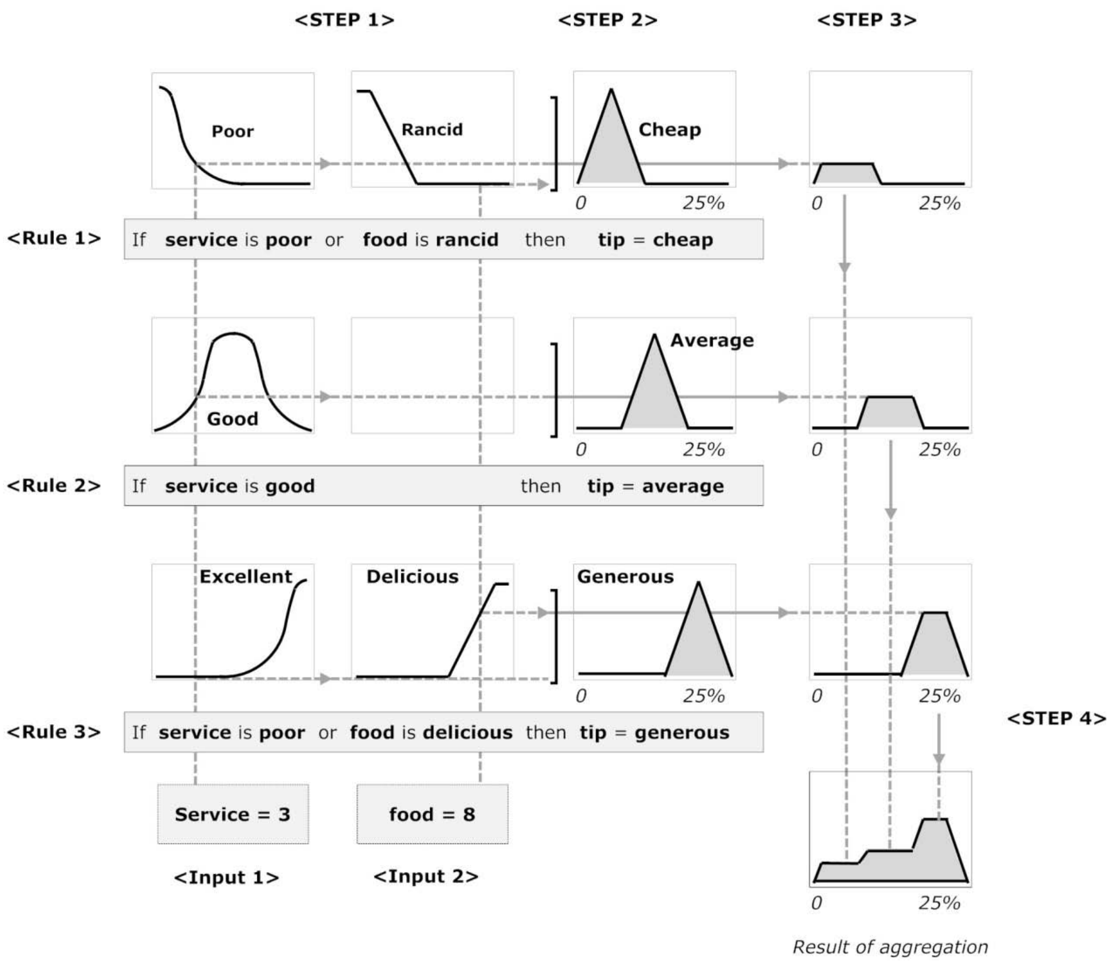


Figure 3-7: Aggregation of Outputs

Step 5 of Fuzzy Inference: Deffizzification

Showed in Figure 3-8, in the computation of defuzzification process, the aggregate output fuzzy set (Step 4) is defuzzifed for a single number. As much as fuzziness helps the rule evaluation during the intermediate steps, the final desired output for each variable is generally a single number. However, the aggregate of a fuzzy set encompasses a range of output values, and so must be defuzzified in order to resolve a single output value from the set.

There are five frequently used methods for defuzzification: centroid, bisector, middle of maximum (the average of the maximum value of the output set), largest of maximum, and smallest of maximum. The most popular method is the gravity centroid calculation, which returns the center of area under the curve.

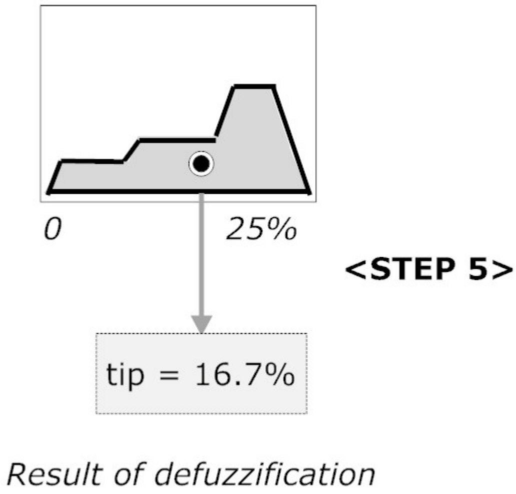


Figure 3-8: Defuzzication

3.3 Decision Tree

3.3.1 Basic Principle

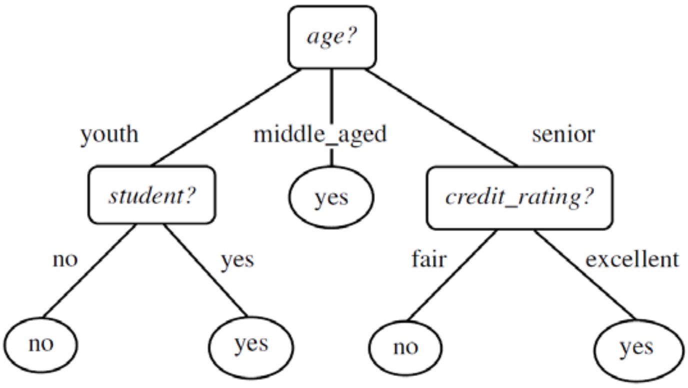


Figure 3-9: A Typical Decision Tree

Decision tree induction is a learning strategy from a set of class-labeled training tuples. A decision tree is a flowchart-like tree structure, where each internal node (non leaf node) denotes a test on an attribute, each branch represents an outcome of the test, and each terminal node (or leaf node) holds a class label. The topmost node in a tree is the root node [HAN & KAMBER, 2006]. A typical decision tree is shown in Figure 3-9.

During the late 1970s and early 1980s, J. Ross Quinlan, a researcher in machine learning, developed the well-known learning algorithm of decision tree, called ID3 algorithm (Iterative Dichotomiser) [QUINLAN, 1986]. This work expanded on earlier work on "concept learning systems", described by E. B. Hunt, J. Marin, and P. T. Stone [HAN & KAMBER, 2006]. Quinlan later presented C4.5 (a successor of ID3), which became a benchmark to which newer supervised learning algorithms are often compared [QUINLAN, 1988]. In 1984, a group of statisticians published the book "Classification and Regression Trees" (CART), which described the generation of binary decision trees [BREIMAN et al., 1984]. ID3 and CART were invented independently of one another at around the same time, yet follow a similar approach for learning decision trees from training tuples. These two cornerstone algorithms spawned a flurry of work on decision tree induction. ID3, C4.5, and CART adopt a greedy (i.e., nonbacktracking) approach in which decision trees are constructed in a top-down recursive divide-and-conquer manner. Most algorithms for decision tree induction also follow such a top-down approach, which starts with a training set of tuples and their associated class labels. The training set is recursively partitioned into smaller subsets as the tree is being built. Differences in decision tree algorithms include how the attributes are selected in creating the tree and the mechanisms used for pruning. [HAN & KAMBER, 2006].

In my research project, in the process of modeling and analysis of human perceptual data, two different learning algorithms of decision trees, CART and Fuzzy-ID3, are used to generate rule bases for building the models. The procedures of these two algorithms are discussed in the following sections.

3.3.2 General Tree-building Process

Most of decision tree algorithms contain the following general process composed of three key steps [SUKNOVIC et al., 2012]:

Step 1 of General Tree: Generate for a given dataset S possible splitting candidates, i.e. for all attributes X_i $(i = 1, \ldots, m)$ define possible splits (potential nodes branches which are obtained by defining possible cut points for numerical attributes, and possible groupings of categories for categorical attributes).

Step 2 of General Tree: Evaluate the generated splits with a split evaluation measure and choose the best split. Implement the split, i.e. grow the tree with the chosen split as a node in the tree. The dataset S is then divided into disjoint subsets S_j $(j \in 1, \ldots, k)$ where k defines number of branches of the chosen split.

Step 3 of General Tree: Repeat steps 1 and 2 recursively for all branches (S_j) of the tree until tree is grown completely (i.e. all leaves of the decision tree are “pure”) or until another user-defined stopping criteria has been fulfilled.

After this general process has been grown, pruning of trees can be performed additionally to resolve the decision tree model’s over-fitting problem.

3.3.3 CART

Based on the general process of building decision tree, CART grows tree only with binary split. And thus the decision tree produced by CART is deep and narrow. The special features in the three basic steps of CART tree-building process are:

Step 1 of CART: Generate all possible splitting candidates (i.e. attributes). For numerical attributes, all possible splits have to be considered, which are always binary. For categorical attributes, all possible binary groupings of attributes should be generated.

Step 2 of CART: Evaluate the generated splits based on a chosen evaluation measure. In general, threre are three splitting methods for CART decision tree, which are Gini, Twoing, and Least Squares Deviation. The first two splitting methods are used for the categorical classies. And the last method is used for the continuously classification. In our case, we select towing for splitting measures because our final classes are categorical. Furthermore, Gini is unstable and more easy to over fit than Twoing [KANTARDZIC, 2011].
The concern indexes and rule [MATHEWORKS, 2011] are as the following:

a) **Twoing measure:** Twoing is not a purity measure of a node, but is a different measure for deciding how to split a node. Let $L(i)$ denote the fraction of members of class i in the left child node after a split, and $R(i)$ denote the fraction of members of class i in the right child node after a split. Choose the split criterion to maximize, which is expressed by

$$T = P(L)P(R)\left\{\sum_i |L(i) - R(i)|\right\}^2$$

where $P(L)$ and $P(R)$ are the fractions of observations that split to the left and right respectively. If the expression T is large, the split made each child node purer. Similarly, if the expression T is small, the split made each child node similar to each other, and hence similar to the parent node, and so the split did not increase node purity.

b) **Node error:** The node error is the fraction of misclassified classes at a node. If j is the class with largest number of training samples at a node, the node error is

$$Error = 1 - p(j)$$

Step 3 of CART: Steps 1 and 2 are repeated recursively as in all other trees until stopping criteria have been reached.

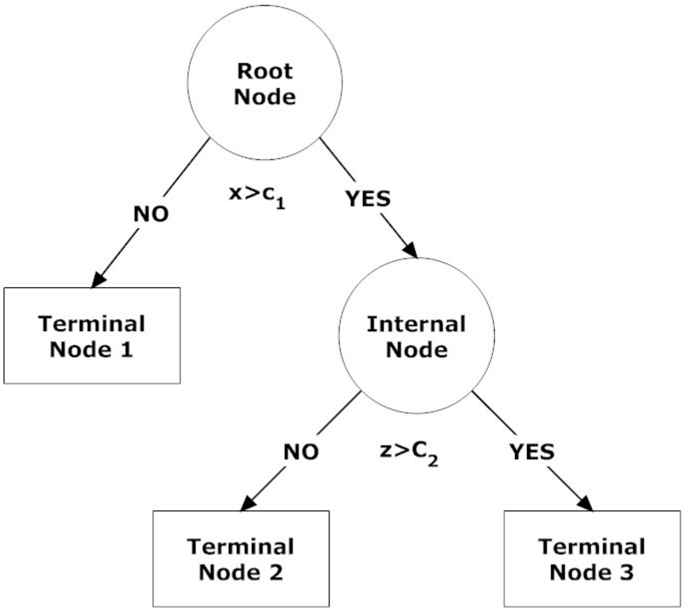


Figure 3-10: Structure of CART Decision Tree [BERK, 2008]

In the Figure 3-10, a typical CART decision tree is presented by binary structure. On the root node or an internal node (also called a sub node), there is a classification done for one attribute. For example, on the root node, we classify the whole dataset into two subsets, i.e. $x > c_1$ for the branch "Yes" and $x \leq c_1$ for the branch "No". On each terminal node (also called a leaf) is located a class, in which all learning data have the same belonging and can not be further split. This class can be represented by either its category label or its numerical representative value.

In practice, the advantages of CART algorithm can be described as [BRAMER, 2007]:

a) It's easy to understand what variables (the attributes in the trees) are important in making the prediction.
b) If some data is missing, we might not be able to go all the way down the tree to a leaf, but we can still make a prediction by averaging all the leaves in the sub-tree we can reach.
c) The model gives a jagged response, so it can work when the true regression surface is not smooth. If it is smooth, though, the piecewise-constant surface can approximate it arbitrarily closely (with enough leaves)

d) It is a fast and reliable algorithm to general trees.

3.3.4 Fuzzy-ID3

Fuzzy decision trees aim at high comprehensibility normally attributed to ID3, with the gradual and graceful behavior attributed to fuzzy systems. Thus, they extend ID3 procedure, using fuzzy sets and approximate reasoning both for the tree-building and the inference procedures [JANIKOW, 1996].

The features and rules in the process of ID3 algorithm are

STEP 1 of Fuzzy ID3: Splits creation in form of multiply splits, i.e. for every attribute a single split is created where attributes' categories are branches of the proposed split.

STEP 2 of Fuzzy ID3: Evaluation of best split for tree branching based on measure based on entropy and information gain, which are defined by

a) Entropy: in a node, the entropy measure can be expressed by [SHANON, 1948]

$$E(S) = -\sum_{i=1}^{C}[P(i)\log_2 P(i)]$$

where C represents the number of classes as the output variable, and $P(i)$ is the probability of the $i-th$ class. S denotes the learning dataset in a node.

b) Information gain: ID3 uses information gain $I(X,S)$, as a measure of split quality measure, which is calculated by

$$E(A,S) = \sum_{j=1}^{K}\left(\frac{|S_j|}{|S|}\cdot E(S_j)\right)$$

$$I(A,S) = E(S) - E(A,S)$$

Where $E(A,S)$ is the expected entropy of an input attribute A that has K categories, $E(S_j)$ is the entropy responding to a certain category j of A, and $\frac{|S_j|}{|S|}$ is the probability of the $j-th$ category in the attribute A. $I(X,S)$, representing the information gain of attribute A represents the amount of information held by attribute A for the class disambiguation. Furthermore, for all the attributes A's in one node, the node is split by using the most discriminatory attribute, whose information gain is maximal.

STEP 3 of Fuzzy ID3: Checking of the stop criteria, and recursively applying the steps 1 and 2 for generating new branches.

In classical decision trees, created by the ID3 algorithm, attributes can have only symbolic or discrete numerical values. In case of fuzzy decision trees attributes can also have linguistic values represented by fuzzy sets. Fuzzy decision trees have been obtained as a generalization of classical decision trees through application of fuzzy sets and fuzzy logic. The Fuzzy-ID3 algorithm is an extension of ID3 algorithm. The difference between these two algorithms is in the method of computing the probability count of learning examples in each node.

In the Fuzzy-ID3 algorithm [JANIKOW, 1996] [BARTCZUK & RUTKOWSKA, 2006], the total examples count P in the node N are expressed as:

$$P=\sum_{j=1}^{L}P_j$$

where $1,\dots,L$ are corresponding to linguistic values for the decision attribute A. Assume x_i and y_i are input vector and output value, which correspond to attributes and class, respectively, and the examples count P_j for the $i-th$ class is determined as follows:

$$P_j=\sum_{i=1}^{C}f\left(\mu^{\circ}(x_i),\mu_j(c_i)\right)$$

where f is the function employed to compute the value of fuzzy relation (we use the Min operator). μ° is membership function of Cartesian product of fuzzy sets that appear on the path from the root node to node N and μ_j is membership function of fuzzy set that determines class c_j.

Different from the ID3 algorithm, the equations of entropy takes the following forms:

$$E(S) = -\sum_{j=1}^{L} \frac{P_j}{P} \log_2 \frac{P_j}{P}$$

$$E(A,S) = \frac{\sum_{k=1}^{R} P_k^A \, E(k,S)}{\sum_{k=1}^{R} P_k^A}$$

where P_k^A is total count of examples in node N concerning the linguistic value k of the attribute A, which has R linguistic values. The stopping conditions are the same as in the ID3 algorithm.

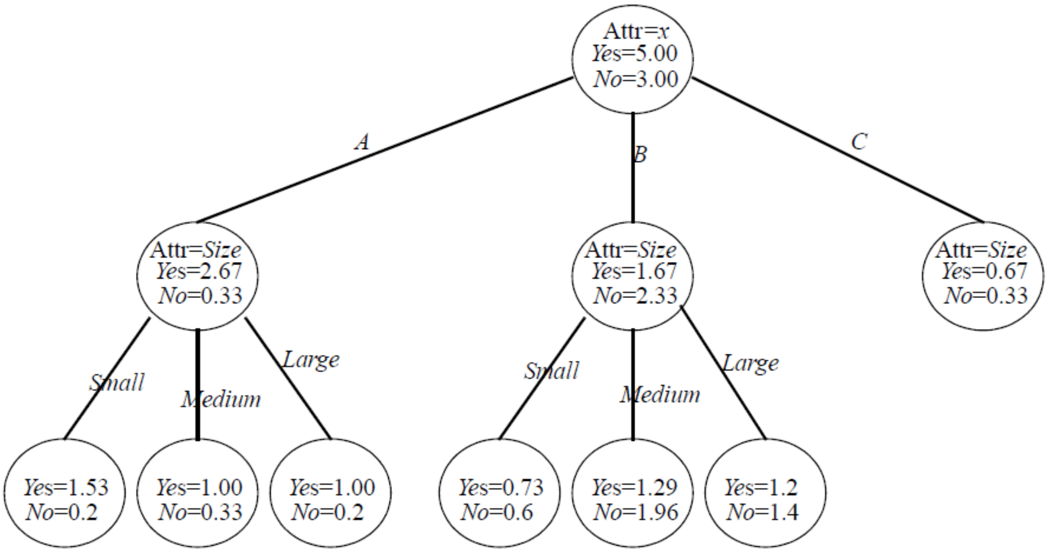


Figure 3-11: Structure of Fuzzy-ID3 Decision Tree [JANIKOW, 2007]

Figure 3-11 shows a typical decision tree generated by fuzzy-ID3 algorithm, it is a two-layer tree, which has two classes, “Yes” or “No”. In the first layer, the root node has three branches, which correspond respectively to the three categorical items (A, B, C) of the attribute x. In the second layer, the internal nodes generate their branches according to the linguistic values (Small, Medium, Large) of the attribute “Size”. On each terminal node, an attribute value corresponds to each class. This value is calculated based on probability of learning examples and fuzzy operation.

In CART decision tree, each path from root node to terminal node is only for one class. In fuzzy-ID3 decision tree, the terminal node of each path presents different memberships of all the classes.

Most traditional decision tree methods (such as CART, ID3), which are used for extracting knowledge in classification problems, can not deal with cognitive uncertainties such as vagueness and ambiguity associated with human thinking process and perception. However, fuzzy decision trees (such as Fuzzy-ID3) can represent classification knowledge more naturally to the way of human thinking. They are more robust in tolerating imprecise, conflict, and missing information for treat the problems of cognitive uncertainties [YUAN & SHAW, 1995].

3.4 Fuzzy Cognitive Map

In the 1970s, political scientist Robert Axelrod introduced cognitive maps for representing social scientific knowledge [AXELROD, 1976]. Showed in Figure 3-12, Axekrod's cognitive maps are signed digraphs. Nodes are variable concepts. Appositive edge form node A to node B means A causally increases B. A negative edge from A to B means A causally decrease B.

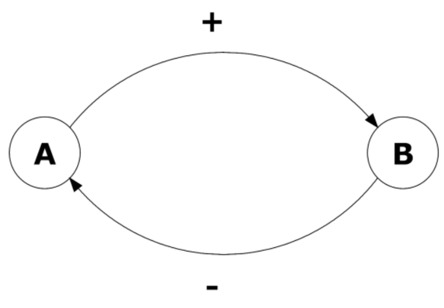


Figure 3-12: A Simple Example of Axekrod's Cognitive Map

Based on the Axekrod's cognitive map, Bart Kosko introduced the fuzzy cognitive map in

1986. It is a fuzzy-graph structure for representing causal reasoning [KOSKO, 1986].

Most knowledge is specification of classifications and causalities. In general, the classes and causalities are uncertain (usually fuzzy or random). The fuzziness passes into knowledge representations and on into knowledge bases, where it leads to a knowledge acquisition or processing tradeoff. If the knowledge representation is fuzzier, the knowledge acquisition is easier and the knowledge-source concurrence is greater. But the knowledge processing is harder. The fuzziness of fuzzy cognitive map allows hazy degrees of causality between hazy causal objects (concepts). Its graph structure allows systematic causal propagation, in particular forward and back ward chaining, and it allows applicable in soft knowledge domains, where both the system concepts, relationships and the meta-system language are fundamentally fuzzy [KOSKO, 1986].

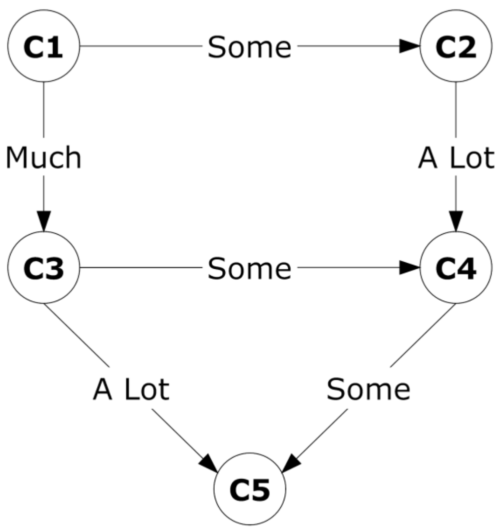


Figure 3-13: A Example of Fuzzy Cognitive Map

The example of a typical fuzzy cognitive map in Figure 3-13, has five concepts which are represented by C_1, C_2, C_3, C_4, C_5. Their causal relationships are expressed by the arcs with fuzzy linguistic values {“None”, “Some”, “Much”, “A Lot”}.

According to the directions of the arcs, from C_1 to C_5, there are three causal paths:

$P_1 \rightarrow (arc_{13}, arc_{35})$

$P_2 \rightarrow (arc_{13}, arc_{34}, arc_{45})$

$P_3 \rightarrow (arc_{12}, arc_{24}, arc_{45})$

So the three effects of C_1 on C_5 by the paths

$\mathrm{I}(P_1) = min\{Much, A\ Lot\} = Much$

$\mathrm{I}(P_2) = min\{Much, Some, Some\} = Some$

$\mathrm{I}(P_3) = min\{Some, A\ Lot, Some\} = Some$

Finally, the total effect of C_1 on C_5 is

$\mathrm{T}(C_1, C_5) = \max\{\mathrm{I}(P_1), \mathrm{I}(P_2), \mathrm{I}(P_3)\} = \max\{\mathrm{Much}, \mathrm{Some}, \mathrm{Some}\} = \mathrm{Much}$

In words, it means C_1 impacts much causality to C_5.

In order to be formalized more easily for calculation, a fuzzy cognitive map with n concepts can be generally represented by a $(n \times n)$-dimensional fuzzy relation matrix

.

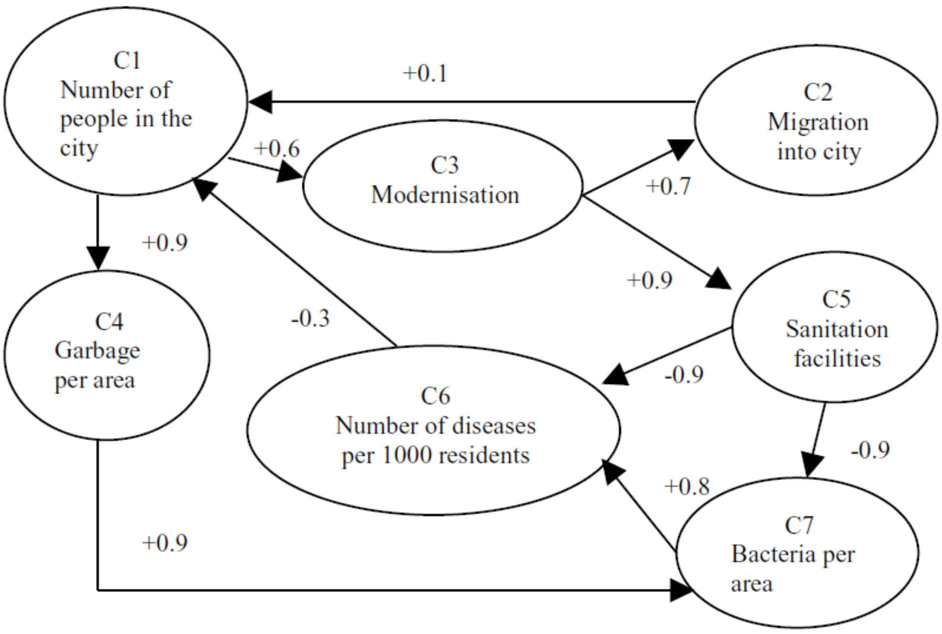


Figure 3-14: Example of Fuzzy Cognitive Map [HAGIWARA, 1992]

In Figure 3-14, the fuzzy cognitive map about public health issue in a city can be expressed by the following fuzzy matrix.

	C1	C2	C3	C4	C5	C6	C7
C1	0	0	0.6	0.9	0	0	0
C2	0.1	0	0	0	0	0	0
C3	0	0.7	0	0	0	0	0
C4	0	0	0	0	0	0	0.9
C5	0	0	0	0	0	-0.9	-0.9
C6	-0.3	0	0	0	0	0	0
C7	0	0	0	0	0	0.8	0

As the extension of cognitive map with the additional capability of representing feedback through weighted causal links, fuzzy cognitive map have been used for representing, analyzing and aiding decision-making in practices of many fields (such as finance, medicine, politics and so on) [VASANTHA KANDASAMY & SMARANDACHE, 2003], [PAPAGEORGIOU et al., 2008].

The decision problems are usually characterized by numerous issues or concepts interrelated in complex ways. Fuzzy cognitive map can represents human knowledge and cognition in a form that lends itself to relatively easy integration into a collective knowledge base for a group involved in a decision process [KHAN & QUADDUS, 2004]. And furthermore, it can be easy to aggregate the knowledge of various experts by using fuzzy relation operation [PAPAGEORGIOU et al., 2008].

3.5 Conclusion

The previously presented three computational tools (fuzzy sets theory, decision tree, fuzzy cognitive map) will be applied in the modeling of the proposed fashion design support system for realizing different functions. They have been carefully selected according to the nature of the involved data and relations.

The human perception, including expert knowledge and consumer cognition, is often conceptual and ambiguous, which is difficult to be characterized by using classic computational tools such as statistics. In this context, fuzzy sets theory will be more efficient for formalizing perceptual data, relations between concepts and other uncertain problems in the design process.

The relation between body measurements or body ratios and normalized sensory descriptors is more concerned by professional designers during their design process. It is a complex relation and experts can only give evaluation scores on specific human bodies according to their perceptions but they can not provide rationalized rules characterizing this relation. In this context, we need an empirical model for extracting rules directly from experimental data. Decision trees have been selected for modeling this relation due to its simplicity, capacity of interpretation and learning from a small set of data. In practice, acquisition of a huge quantity of learning data related to human perception is difficult and time-consuming. Moreover, the results of a decision tree are easy to be understood.

The relation between fashion themes and sensory descriptors describing body shapes is more close to consumer requirements. In fact, consumers need a fashion product to improve his/her personal social image towards a desired fashion theme. This relation is characterized by consumers according to their cognitive knowledge and self-image. In this context, fuzzy cognitive map is an efficient tool for representing human knowledge and cognitions on relations between abstract fashion themes and specific body shapes. It offers a good approach to the stimulation and aggregation of human perceptions provided by multiple evaluators.

Chapter 4 Formalization and Modeling of Human Perception

Having acquired human perceptual data from both experts and consumers using the three experiments described in Chapter 2, we give in this chapter the mathematical formalization of the concerned concepts and model the relations between fashion themes, sensory descriptors describing human body shapes, and body ratios. The objective is to formally characterize the perception of a naked human body and that of the human body with garment in order to propose the most suitable design style for promoting the image of the specific wearer.

4.1 Mathematical Formalization

Let $T = \{t_1, t_2, \ldots, t_n\}$ be a set of n fashion themes characterizing the socio-cultural categories of body shapes. In my project, we have identified three fashion themes (*n*=3) in sensory evaluation, which are “sporty”, “nature” and “attractive”.

Let $D = \{d_1, d_2, \ldots, d_m\}$ be a set of *m* basic sensory descriptors extracted by the fashion experts for describing the fashion themes in T. In previous sensory evaluation, 22 sensory descriptors have been extracted for describing body shapes.

Let $W = \{w_1, w_2, \ldots, w_p\}$ be a set of p virtual body shapes generated by using the software LECTRA-Modaris 3D fit.

Let $BM = \{bm_1, bm_2, \ldots, bm_h\}$ be a set of h body measurement features characterizing human body shapes. The body measurements of all the p virtual body shapes in W constitutes a matrix, denoted as $(bm_{ij})\ h \times p$ with $i = 1, \ldots, h, j = 1, \ldots, p$.

Let $BR = \{br_1, br_2, \ldots, br_g\}$ be a set of g body ratio indexes calculated from the body measurements of the set B. The body ratios of all the p virtual body shapes in W also constitutes a matrix, denoted as $(br_{ij})\ g \times p$ with $i = 1, \dots, g, j = 1, \dots, p$.

Let $EX = \{ex_1, ex_2, \dots, ex_r\}$ be a set of r evaluators (design experts) evaluating the relevancy of sensory descriptors to virtual body shapes (naked or with garment). For any given sensory descriptor, each evaluator compares each virtual body shape with the standard body shape CA170 by selecting a linguistic score from { C_1 (*very inferior*), C_2(*inferior*), C_3(*fairly inferior*), C_4(*a little inferior*), C_5(*neutral*), C_6(*a little superior*), C_7(*fairly superior*), C_8(*superior*), C_9(*very superior*)}.

Let $EC = \{ec_1, ec_2, \dots, ec_z\}$ be a set of z evaluators (consumers) evaluating the relevancy between fashion themes and sensory descriptors. For any specific sensory descriptor and fashion theme, each evaluator gives a degree of their relevancy by selecting a linguistic score from the set {R_1(*very irrelevant*), R_2(*fairly irrelevant*), R_3(*neutral*), R_4(*fairly relevant*), R_5(*very relevant*)}.

Let $S = \{s_1, s_2, \dots, s_\xi\}$ be a set of ξ existing garment styles which will be used as references in the design process. In our experiment, we give five reference styles for men's overcoat, which are "Chester", "Ulster", "Balmacaan", "Trench" and "Duffle".

Let $DE = \{de_1, de_2, \dots, de_\lambda\}$ be a set of λ new garment styles generated for a special body shape. These new styles are generated by making combinations of the reference styles. It can be given in the form of photos or sketches by fashion designers.

4.2 Model I: Characterization of the Relevancy of Body Ratios (Naked Bodies) to a Fashion Theme

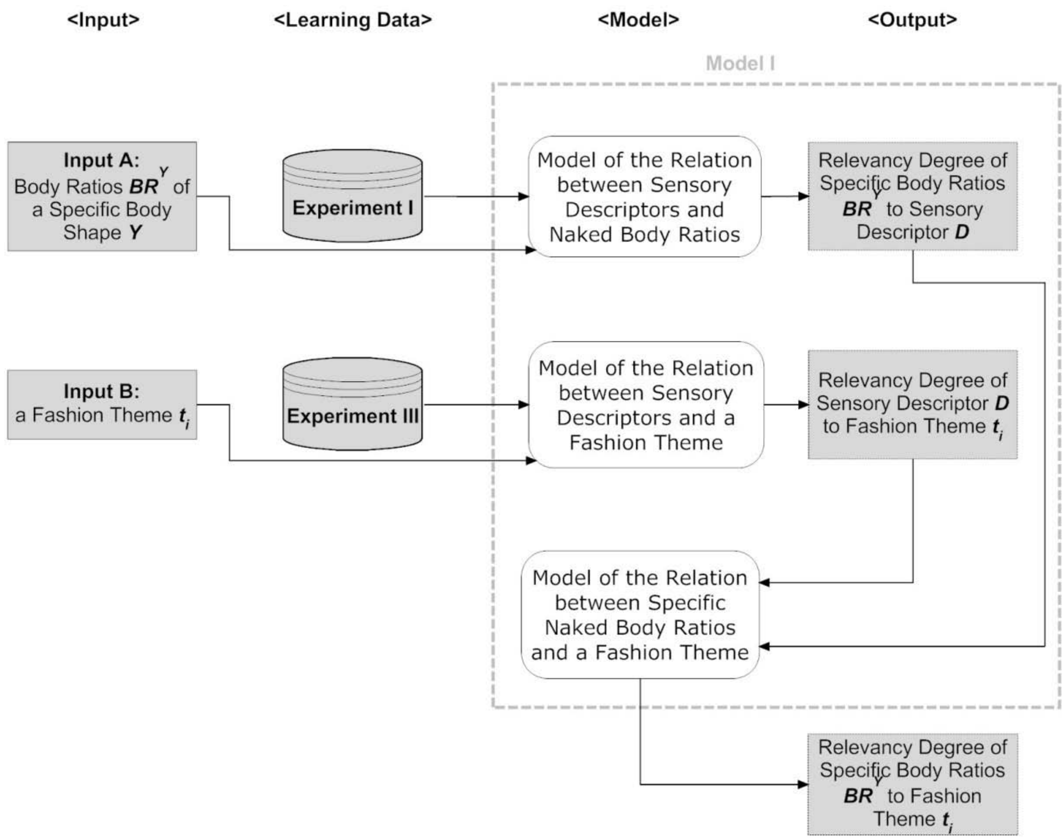


Figure 4-1: Functional Structure of **Model I**

The data flow of **Model I** is presented by its functional structure in Figure 4-1. The details of modeling for each component are given in the following sections.

4.2.1 Relation between Sensory Descriptors and Body Ratios (Naked Bodies)

Stage 1 of R_D-BR: Building Decision Trees

Having acquired the body measurements and the dissimilarity degrees related to one sensory descriptor d_j for all the p virtual body shapes, obtained in **Experiment I** in Chapter 2, we use decision trees for deducing or predicting the relation between one sensory descriptor d_j and the body ratios BR's of body shape. We build one decision tree TR_{ij} for each sensory descriptor d_j and each evaluator ex_i by learning from the evaluated data of all the p representative virtual body shapes. In the procedure of decision tree construction, two learning algorithms, i.e. CART and Fuzzy-ID3 introduced in Chapter 3 have been used respectively for learning from the same learning data. The performance of these two algorithms are analyzed and compared at the end of this chapter.

1) CART Decision Tree:

As discussed in Chapter 2, body ratios are more significant than body measurements, especially when evaluating body shapes from the view of aesthetics [FAN, 2004]. It is for this reason that we take the body ratios as input variables (attributes) of the decision trees. By making all combinations of the six key body measurements BM's selected in Chapter 2, we obtain 15 body ratios BR's, shown in Table 4-1.

Body Ratios:			
$br_1 \rightarrow$	bm_2/bm_1	$br_9 \rightarrow$	$bm6/bm3$
$br_2 \rightarrow$	bm_3/bm_1	$br_{10} \rightarrow$	$bm5/bm6$
$br_3 \rightarrow$	bm_4/bm_1	$br_{11} \rightarrow$	$bm2/bm4$
$br_4 \rightarrow$	bm_5/bm_1	$br_{12} \rightarrow$	$bm2/bm5$
$br_5 \rightarrow$	bm_6/bm_1	$br_{13} \rightarrow$	$bm2/bm6$
$br_6 \rightarrow$	bm_2/bm_3	$br_{14} \rightarrow$	$bm4/bm5$
$br7 \rightarrow$	bm_4/bm_3	$br_{15} \rightarrow$	$bm4/bm6$
$br8 \rightarrow$	bm_5/bm_3		
bm_1: *Stature*		bm_4: *Neck Circumstance*	
bm_2: *Total Length of Arm*		bm_5: *Waist Circumstance*	
bm_3: *Chest Circumstance*		bm_6: *Hip Circumstance*	

Table 4-1: Selected Body Ratios

Using the algorithm CART, we obtain a set of decision trees TR_{ij} $(i = 1, \dots, r\,; j = 1, \dots, m)$, each having only two branches on each node like the example of Figure 4-2. The threshold values permitting to separate each node can be automatically determined from the

CART algorithm.

In the CART decision tree of Figure 4-2, br_8 (the ratio of Waist Circumstance to Chest Circumstance) is a body ratio (attribute) separating the node. The threshold value 0.8472 of this attribute characterizes the classification result, represented by two linguistic values of Muscular level (C_5 and C_4). Two IF-THEN rules are obtained, i.e.

a) IF Ratio Waist Circumstance Chest Circumstance $<$ 0.8472, THEN the corresponding *Muscular* level is equivalent to the standard body shape (C_5)

b) IF Ratio Waist Circumstance Chest Circumstance $\geq$ 0.8472, THEN the corresponding *Muscular* level is a little inferior to the standard body shape (C_4)

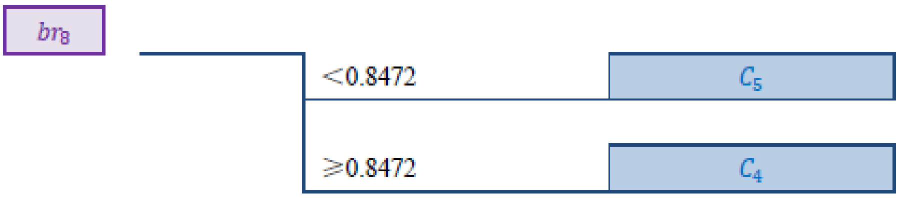


Figure 4-2: Example of CART Decision Tree for the Sensory descriptor "*Sebaceous-Muscular*"

2) Fuzzy-ID3 Decision Tree:

According to the discussion in Chapter 3, fuzzy decision trees are more efficient for treating learning data of mixed type, including both numerical and categorical data. When processing numerical learning data like body ratios with a fuzzy decision tree, the corresponding attributes should be fuzzified and then computed as linguistic variables.

In my project, the procedure of the fuzzification is given below.

Step 1 of Fuzzy-ID3: Normalization of Body Ratios

We normalize all the numeric values of body ratios br_i's into the range of 0 and 1 by using

$br_i := br_i/\delta_i$.The weight δ_i is added so that all learning data can be more uniformly distributed in [0, 1]. For each body ratio br_i, the corresponding weight δ_i in our calculation is defined in [HAN & KAMBER, 2006], we have

$$\delta_i = \sqrt{\sum_{j=1}^{p} br_{ij}^2} \ (i = 1, \dots, m)$$

Step 2 of Fuzzy-ID3: Setting Linguistic Values:

The linguistic set {VS (very small), S (small), M (medium), L (large), VL (very large)} is used for fuzzification of all the body ratios.

Step 3 of Fuzzy-ID3: Creating Membership Functions:

For each normalized body ratio, the membership functions for its five linguistic values are defined as follows.

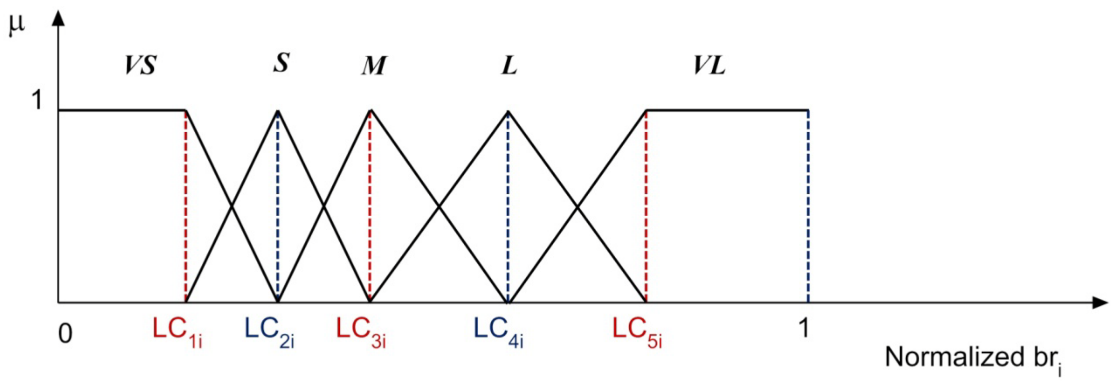


Figure 4-3: Membership Function of Normalized Body Ratio

Shown in Figure 4-3, for any normalized body ratio br_i, the triangular membership functions are characterized by the parameters $LC_{1i}, \dots, LC_{5i}$. Considering the real distribution of the learning data, i.e. the body ratios measured on the 12 virtual body shapes, we define

$LC_{1i} = Min\{br_{ij} | j = 1, \dots, p\}$

$LC_{5i} = Max\{br_{ij} | j = 1, \dots, p\}$

$LC_{3i} = Standard(br_i)$

$LC_{2i} = \frac{LC_1^i + LC_3^i}{2}$

$LC_{4i} = \frac{LC_3^i + LC_5^i}{2}$

Where LC_{1i} takes the minimal value of the body ratio br_i's of all the 12 virtual body shapes, LC_{3i} the value of br_i of the standard body shape CA170, LC_{5i} the maximal value of br_i's, LC_{2i} the average of LC_{1i} and LC_{3i}, and LC_{4i} the average of LC_{3i} and LC_{5i}.

Step 4 of Fuzzy-ID3: Converting a numerical value into fuzzy value

When a specific numerical value x of br_i is introduced, we compute its corresponding membership degrees from Figure 4-5. The fuzzy value of x can be expressed by

$$x \to \left(\mu_i^{VS}(VS), \mu_i^{VS}(S), \mu_i^{VS}(M), \mu_i^{VS}(L), \mu_i^{VS}(VL)\right)$$

And then this fuzzy value will be used in the implication of Fuzzy-ID3 algorithm.

Unlike classical decision trees, leading to cover only one path from the root to a leaf for a specific input vector, a fuzzy decision tree TR_{ij} generated from the Fuzzy-ID3 learning algorithm permit to cover all the possible paths to the leafs with different membership degrees. An example of our Fuzzy-ID3 decision tree is shown in Figure 4-4.

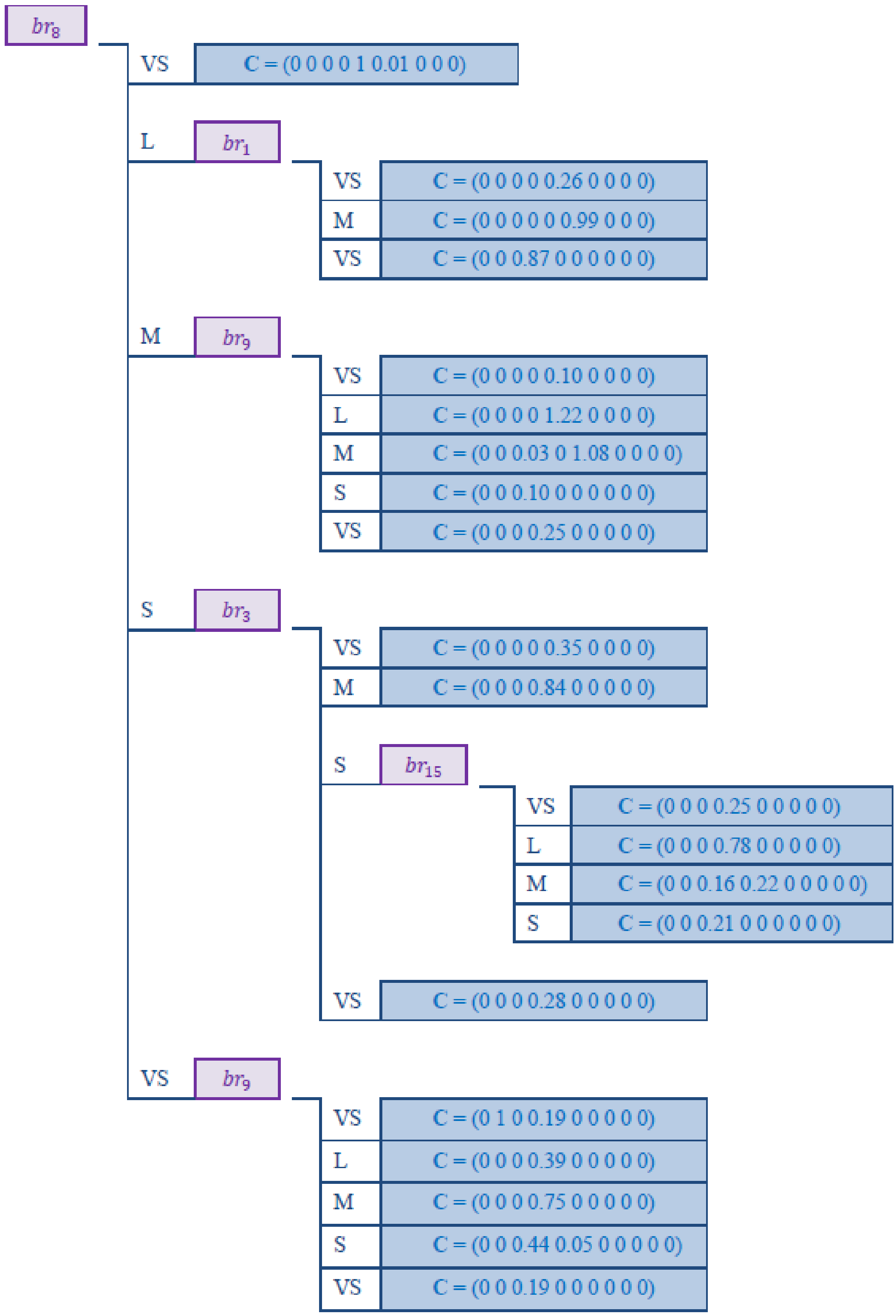


Figure 4-4: Example of Fuzzy-ID3 for the Sensory descriptor "*Sebaceous-Muscular*"

From the Fuzzy-ID3 decision tree, one extracted fuzzy rule can be expressed by

IF BR_8 (Ratio Waist Circumstance/Chest Circumstance) = Large (L) AND BR_3 (Ratio Neck Circumstance/Stature) = Large (L) AND BR_{15} (Ratio Neck Circumstance/Hip Circumstance) = Medium (M), THEN the corresponding *Muscular* level is (0 0 0.16 0.22 0 0 0 0 0)

The consequence of this rule means that *Muscular* level belongs to C_3 with a membership degree 0.16, to C_4 with a membership degree 0.22, and there is no possibility of belonging to the other classes.

Stage 2 of R_D-BR: Aggregation of Decision Trees

1) CART Decision Trees:

In a CART decision tree, the body ratios of any specific person *Y*, $BR^Y = (br_1^Y, br_2^Y, \dots, br_g^Y)$, can be easily measured by applying Table 4-1. If Y can be represented by the combination of all the existing virtual body shapes $w_1, w_2, \dots, w_p$, we obtain only one rule of TR_{ij} corresponding to *Y*. If *Y* can not be covered by these virtual body shapes, there is no rule of TR_{ij} exactly corresponding to *Y*. Anyway, we can always find a rule of TR_{ij} the closest to *Y*. It is expressed by

RL_{ij}: IF $\{(br_1^Y Comp_1 v_1)$ OR $u_1\}$ AND … AND $\{(br_g^Y Comp_g v_g)$ OR $u_g\}$, THEN the evaluation result IS C_{ij}.

where $br_1^Y, br_2^Y, \dots, br_g^Y$ denote the variables for body ratios of Y; $v_1, v_2, \dots, v_g$ the corresponding threshold values separating each node into two branches, $\mathrm{Comp}_1, \mathrm{Comp}_2, \dots, \mathrm{Comp}_g$ are the comparators (< or >); $\mathrm{u}_1, \dots, \mathrm{u}_g$ denote the Boolean values related to the existence of the body ratios ($\mathrm{u}_k = 0$ if br_k^Y appears in the rule then and $u_k = 1$ otherwise), C_{ij} the classes equivalent to the evaluation score given by ex_i for the descriptor d_j. Its value is taken from $\{C_1, \ldots, C_9\}$.

For a specific sensory descriptor d_j, we obtain *r* rules each corresponding to one evaluator (expert). The relevancy degree of the body ratios BR^Y related to d_j can be defined as follows.

The relevancy degree of the body ratios $BR^Y = (br_1^Y, br_2^Y, \ldots, br_g^Y)$ related to the rule RL_{ij} can be defined by

$$RE_{ij} = \mathrm{Min}\{RE_{ij\,1}, RE_{ij\,2}, \ldots, RE_{ij\,h}\}$$

with

$$RE_{ijk} = \begin{cases} 1 & if\ u_k = 1\ and\ (br_k^Y\, Comp_k\, v_k) \\ 1 - |br_k^Y - v_k| / |\mathrm{Max}\{br_{k1}, \ldots, br_{kp}\} - \mathrm{Min}\{br_{k1}, \ldots, br_{kp}\}| & otherwise \end{cases}$$

where, the relevancy degree RE_{ij} is obtained by comparing the body ratios of Y with the corresponding threshold values on the nodes of the decision tree TR_{ij}. Its values vary between 0 and 1. RE_{ijk} is the relevancy degree of br_k^Y (the *k*-th body ratio of *Y*) related to the corresponding threshold value v_k of the rule RL_{ij}.

There is an error case: $|br_k^Y - v_k| / |\mathrm{Max}(BR_k^W) - \mathrm{Min}(BR_k^W)| > 1$. In this case, the comparison between br_k^Y and v_k is out of the range of all the *k*-th body ratios of the virtual body shapes, i.e. $br_{k1}, \ldots, br_{kp}$, meaning that RL_{ij} is totally incapable of classifying br_k^Y. Then, we define $RE_{ijk} = 0$ leading to $RE_{ij} = 0$.

Next, we aggregate the evaluation results C_{ij}'s given by all the *r* evaluators. The corresponding weights are the relevancy degrees RE_{ij}. The aggregated relevancy degree of the body measurements of *Y* related to the sensory descriptor d_j is defined by

$$RE_j = \sum_{i=1}^{r} RE_{ij}\left(C_{ij}\right) / \sum_{i=1}^{r} RE_{ij}$$

As C_{ij}'s are linguistic values taken from $\{C_1, C_2, \ldots, C_9\}$, we distribute the aggregated results on these values and then re-write the above equation below.

$RE_j = \left(\mu_j(C_1)\ \mu_j(C_2)\ \ldots\ \mu_j(C_9)\right)$

with $\mu_j(C_k) = \sum_{i\in\Omega_k^j} RE_{ij} \ / \sum_{i=1}^{r} RE_{ij}$

and $\Omega_k^j = \left\{i \middle| i \in \{1,2,\ldots,r\}\ and\ C_{ij} = C_k\right\}$ for $k = 1,2,\ldots,9$

RE_j can be considered as a fuzzy set. For all the sensory descriptors $d_1, d_2, \ldots, d_m$ we can obtain a fuzzy relation between these sensory descriptors and the body ratios, i.e. $REL(D, BR^Y) = (RE_1^{\mathrm{T}}, RE_2^{\mathrm{T}}, \ldots, RE_m^{\mathrm{T}})^{\mathrm{T}}$. For simplicity, it is rewritten by a ($m \times 9$) dimensional matrix

$$REL(D, BR^Y) = \begin{bmatrix} \mu_1^Y(C_1) & \cdots & \mu_1^Y(C_9) \\ \vdots & \ddots & \vdots \\ \mu_m^Y(C_1) & \cdots & \mu_m^Y(C_9) \end{bmatrix}$$

2) Fuzzy-ID3 Decision Tree:

Assuming that there exist t paths in the fuzzy decision tree TR_{ij} for the special body shape Y, we extract t fuzzy rules as follows.

RL_{ij}^{τ}: IF $\{(br_1^Y$ IS $v_1)$ OR $u_1\}$ AND … AND $\{(br_g^Y$ IS $v_g)$ OR $u_g\}$

THEN the classification result IS $\rho_{ij}^{\tau}\left(C_{ij}^{\tau}\right)$ with $\tau \in \{1,2,\ldots,t\}$

Different from the previous CART decision tree which separates each node into two branches with a numerical threshold (crisp partition), v_k's ($k = 1,2,\ldots,g$) are the linguistic values separating the nodes of TR_{ij} into multiple branches. They take values from the set {VS (very small), S (small), M (medium), L (large), VL (very large)}. In fact, each node corresponds to a fuzzy partition of a numerical body ratio and each branch corresponding to one of its fuzzy values. $u_1, u_2, \ldots, u_g$ are the Boolean values related to the existence of the body ratios, defined in the same way as the CART algorithm. C_{ij}^{τ} are the linguistic values taken from $\{C_1, C_2, \ldots, C_9\}$. $\rho_{ij}^{\tau}(C_{ij}^{\tau})$ can be represented by

$$\rho_{ij}^{\tau}(C_{ij}^{\tau}) = \{\rho_{ij}^{\tau}(C_1), \rho_{ij}^{\tau}(C_2), \ldots, \rho_{ij}^{\tau}(C_9)\}$$

where $\rho_{ij}^{\tau}(C_1), \rho_{ij}^{\tau}(C_2), \ldots, \rho_{ij}^{\tau}(C_9)$ are the membership degrees of the path RL_{ij}^{τ} related to the linguistic values $C_1, C_2, \ldots, C_9$ respectively. They are calculated according to the algorithm of Fuzzy-ID3 [JANIKOW, 1996]. If $\rho_{ij}^{\tau}(C_k)$ $(k \in \{1, 2, \ldots, 9\})$, there is no possibility that the path RL_{ij}^{τ} belongs to C_k. Unlikely the classical CART decision tree which generates only one linguistic value on a leaf, this fuzzy decision tree generates a combination of all predefined linguistic values on each of its leaves. The corresponding membership degrees can be considered as weights of these linguistic values.

When applying the fuzzy decision tree to the special body shape Y, t fuzzy rules (t paths) will be evaluated. The Mamdani method is then used for making fuzzy inference, i.e. aggregation of the evaluation results of these *t* fuzzy rules. Finally, we use the gravity centoid, given in Chapter 3 for defuzzification.

The aggregated fuzzy set C_{ij} is denoted as

$C_{ij} = \left(\mu_{ij}(C_1), \ldots, \mu_{ij}(C_9)\right)$ with $\sum_{k=1}^{9} \mu_{ij}(C_k) = 1$.

Next, we further aggregate the fuzzy sets C_{ij} 's given by all the r evaluators and obtain

$RE_j = \left(\mu_j(C_1), \ldots, \mu_j(C_9)\right)$

with $\mu_j(C_k) = \sum_{i=1}^{r} \mu_{ij}(C_k) / \sum_{k=1}^{9} \sum_{i=1}^{r} \mu_{ij}(C_k) = \sum_{i=1}^{r} \mu_{ij}(C_k) \,/\, r$.

For all the sensory descriptors $d_1, d_2, \ldots, d_m$, we obtain a fuzzy relation between these sensory descriptors and the body ratios. It has the same form as that obtained from the CART method, i.e. $REL(D, BR^Y) = (RE_1^{\mathrm{T}}, RE_2^{\mathrm{T}}, \ldots, RE_m^{\mathrm{T}})^{\mathrm{T}}$. It is also a (m×9) dimensional matrix.

4.2.2 Relation between Fashion Themes and Sensory Descriptors

From **Experiment III** of Chapter 2, we have acquired the relations between 3 fashion themes and 22 sensory descriptors from consumer evaluations.

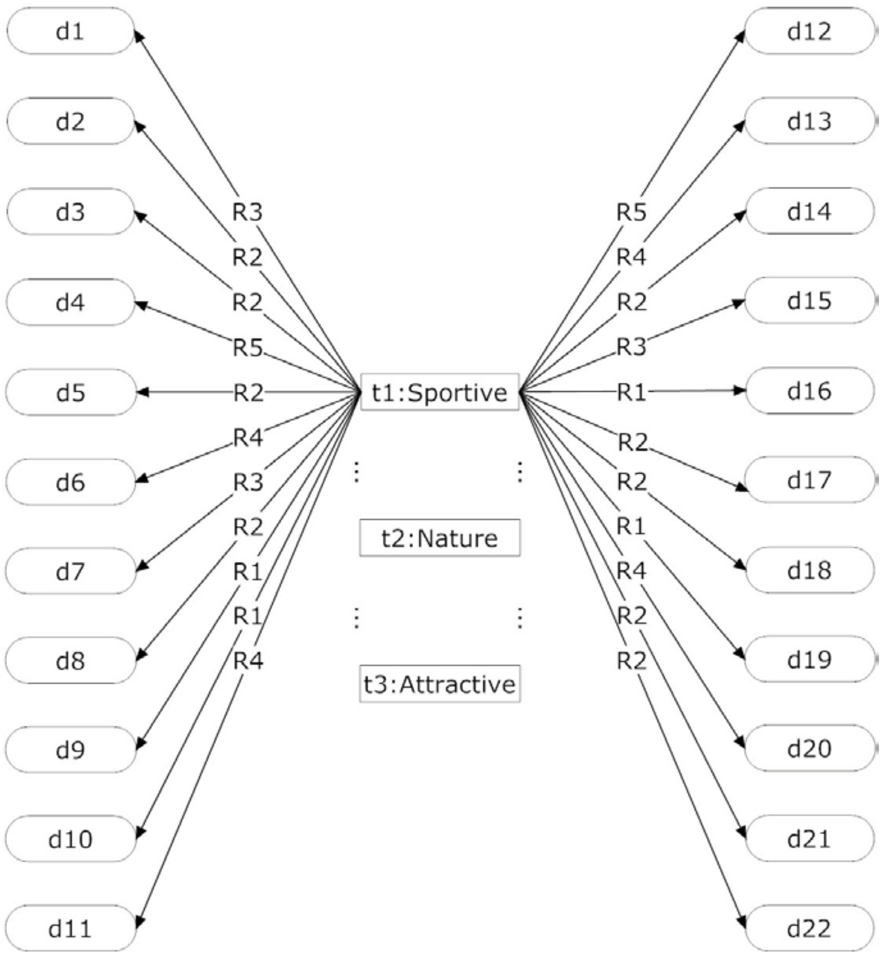


Figure 4-5: Fuzzy Cognitive Map obtained in **Experiment III**

Like the fuzzy cognitive map in Figure 4-5, we obtain one fuzzy cognitive map describing the relation of each fashion theme t_i with the 22 sensory descriptors, provided by one consumer evaluator. Each arc represents an evaluation score and takes values from the set {R_1 = "*very irrelevant*", R_2 = "*fairly irrelevant*", R_3 = "*neutral*", R_4 = "*fairly relevant*", R_5 = "*very relevant*"}.

Next, we aggregate the results of all the z evaluators (consumers) and obtain a possibility distribution characterizing the relation between each fashion theme and each sensory descriptor. The relation between the fashion theme t_i and the sensory descriptor d_j can be expressed by a fuzzy value distributed on the set $\{R_1, R_2, R_3, R_4, R_5\}$, i.e.

$$REL(t_i, d_j) = \left(\frac{NB_{ij}(R_1)}{r}\ \frac{NB_{ij}(R_2)}{r} \dots \frac{NB_{ij}(R_5)}{r}\right) = \{\mu_{ij}(R_1), \mu_{ij}(R_2), \dots, \mu_{ij}(R_5)\}$$

where $NB(R_k)$ is the number of evaluators selecting the linguistic value R_k in their evaluations. Evidently, the sum of all components in $REL(t_i, d_j)$ is 1.

The $(m \times 5)$-dimensional matrix REL_TD_i characterizes the fuzzy relation between a fashion theme t_i and all the sensory descriptors.

$$\begin{aligned} REL(t_i, D) &= (REL(t_i, d_1)^T\ REL(t_i, d_2)^T\ \dots\ REL(t_i, d_m)^T)^T \\ &= \begin{bmatrix} \mu_{i1}(R_1) & \cdots & \mu_{i1}(R_5) \\ \vdots & \ddots & \vdots \\ \mu_{im}(R_1) & \cdots & \mu_{im}(R_5) \end{bmatrix} \end{aligned}$$

For analyzing the distribution of fuzzy relation generated from the sensory evaluation, several criteria of performance, relevancy and dissimilarity are defined as follows.

1) Performance Criteria

The performance of $REL(t_i, d_j)$ can be characterized by the corresponding distribution over the five linguistic values $R_1, \dots, R_5$. The following principles should be taken into account to describe its characters:

a) If it exists more than one peak in the distribution of $EL(t_i, d_j)$, then the evaluation results of different evaluators are diversified and the relationship between the fashion t_i and the sensory descriptor d_j can not be clearly identified by all the evaluators in the same group. Otherwise, all the evaluation data from one group is centered on one peak and the relationship between t_i and d_j can be easily understood.

b) If the width of the distribution of $REL(t_i, d_j)$ is small, then the evaluation results for different evaluators are more concentrated and there is less ambiguity. Otherwise, the ambiguity is more important. The degree of the ambiguity represents the difference of evaluators on perception of products.

According to these principles, we formally define the performance criteria of the relation between the fashion theme t_i and the sensory descriptor d_j by

$$V_{ij}^1 = NB\_Peak(REL(t_i, d_j))$$

and

$$V_{ij}^2 = Var\left(REL(t_i, d_j)\right) = \sum_{k=1}^{5}\left(eq(R_k) - \overline{eq(R_k)}\right)^2 \mu(R_k)$$

$$\overline{eq(R_k)} = \sum_{k=1}^{5} eq(R_k)\mu(R_k)$$

In the previous definition, $NB\_Peak(REL\_TD_{ij})$ and $Var(REL\_TD_{ij})$ denote the number of peaks and the variance of the distribution in REL_TD_{ij} respectively. $eq(R)$'s ($eq(R_1) = 1, \dots, eq(R_5) = 5$) are the equivalence values of the linguistic values $\{R_1, R_2, R_3, R_4, R_5\}$ respectively.

These performance criteria are important in the following analysis because they characterize the quality of evaluation data relating the sensory descriptor d_j to the fashion theme t_i. The performance of the fashion theme t_i can be evaluated by aggregating the performance values corresponding to all the sensory descriptors, i.e.

$$V_i^1 = \frac{1}{m}\sum_{j=1}^{m} V_{ij}^1 \text{ and } V_i^2 = \frac{1}{m}\sum_{j=1}^{m} V_{ij}^2$$

Low values of these criteria mean that the relationship between the fashion theme t_i and all the sensory descriptors is more easily understood by evaluators and the definition of t_i is more relevant to the human perception of evaluators. Otherwise, the fashion theme t_i is less relevant for understanding of evaluators.

Taking the sensory descriptors as basic information representing fashion themes, we can analyze the dissimilarity between them as in the followings text.

2) Relevancy Criterion

The above performance criteria characterize the degree of consistency of the involved consumers related to the relationship between a fashion theme and a sensory descriptor. For the degree of relevancy between a fashion theme and a sensory descriptor, it is defined as the gravity centre of the distribution for all the equivalence values:

$$G\_REL(t_i, d_j) = \sum_k^5 \mu_{ij}(R_k)\, eq(R_k)$$

The values of the projection of $G\_REL(t_i, d_j)$ to the axis of t_i is represented by

$$GP^R\_REL(t_i, d_j) = G\_REL(t_i, d_j) / \sum_k^5 \mu_{ij}(R_k) = \frac{\sum_k^5 \mu_{ij}(R_k) eq(R_k)}{\sum_k^5 \mu_{ij}(R_k)}$$

Bigger the value of $GP^R\_REL(t_i, d_j)$ is, more the sensory evaluation d_j is relevant to the fashion theme t_i.

3) Dissimilarity Criterion

According to the properties of fuzzy relations defined in Chapter 2, the criterion for the dissimilarity of two fashion themes t_1 and t_2 is defined by

$$Dis(t_1, t_2) = H(REL\_TD_{t1}, REL\_TD_{t2}) = \frac{1}{m}\sum_{j=1}^{m} \frac{1}{c}\sum_{\epsilon=1}^{c} \left|\mu_{1j}(R_\epsilon) - \mu_{2j}(R_\epsilon)\right|$$

where H is the Hamming Distance [LEE, 2005], which measures the symmetrical distance between two fuzzy sets. If $Dis(t_1, t_2)$ tends to 0, the two fashion themes t_1 and t_2 are close to each other. If $Dis(t_1, t_2)$ is large enough, the two fashion themes t_1 and t_2 can be considered as quite different.

Sensory Descriptor		Distribution					Performance		Relevancy
		R_1	R_2	R_3	R_4	R_5	V^1	V^2	GP^R
d_{11}	Effeminate-Lusty	0.00	0.04	0.12	0.44	0.40	1	0.0400	4.20
d_{13}	Inelastic-Elastic	0.00	0.08	0.32	0.36	0.24	1	0.0514	3.76
d_{12}	Fragility-Strong	0.00	0.08	0.20	0.32	0.40	1	0.0574	4.04
d_{20}	Lazy-Vivid	0.04	0.04	0.04	0.48	0.40	1	0.0584	4.16
d_8	Non-streamline-Streamline	0.00	0.16	0.32	0.32	0.20	1	0.0604	3.56
d_{21}	Light-Heavy	0.12	0.20	0.32	0.36	0.00	1	0.0646	2.92
d_{19}	Sebaceous-Muscular	0.04	0.04	0.12	0.20	0.60	1	0.0726	4.28
d_4	Atrophic-Forceful	0.04	0.08	0.08	0.28	0.52	1	0.0784	4.16
d_7	Flat-Thick	0.12	0.12	0.28	0.36	0.12	1	0.0864	3.24
d_{10}	Shrive-Fleshly	0.12	0.12	0.24	0.36	0.16	1	0.0936	3.32
d_{17}	Unique-Normal	0.20	0.20	0.32	0.16	0.12	1	0.1000	2.80
d_{16}	Unbalanced-Harmonious	0.08	0.08	0.12	0.24	0.48	1	0.1024	3.96
d_9	Knotty-Smooth	0.16	0.20	0.24	0.24	0.16	1	0.1074	3.04
d_2	Slim-Bulgy	0.08	0.16	0.16	0.24	0.36	1	0.1094	3.64
d_{22}	Unsexy-Sexy	0.20	0.44	0.12	0.20	0.04	2	0.0804	2.44
d_{18}	Unstylish-Stylish	0.16	0.52	0.16	0.04	0.12	2	0.0854	2.44
d_{15}	Cabinet-Huge	0.28	0.24	0.20	0.28	0.00	2	0.0856	2.48
d_{06}	Narrow-Wide	0.28	0.16	0.12	0.44	0.00	2	0.1026	2.72
d_{01}	Thin-Fat	0.16	0.08	0.32	0.24	0.20	2	0.1064	3.24
d_{03}	Dented-Swollen	0.20	0.28	0.08	0.36	0.08	2	0.1084	2.84
d_{14}	Deft-Awkward	0.12	0.24	0.12	0.20	0.32	2	0.1294	3.36
d_5	Short-Tall	0.40	0.20	0.12	0.12	0.16	2	0.1404	2.44

Table 4-2: Rank of Sensory Descriptor for t_1 ("*Sporty*")

Sensory Descriptor		Distribution					Performance		Relevancy
		R_1	R_2	R_3	R_4	R_5	V^1	V^2	GP^R
d_{12}	Fragility-Strong	0.00	0.00	0.36	0.40	0.24	1	0.0366	3.88
d_{18}	Unstylish-Stylish	0.28	0.36	0.32	0.04	0.00	1	0.0466	2.12
d_{19}	Sebaceous-Muscular	0.00	0.20	0.52	0.16	0.12	1	0.0500	3.20
d_{11}	Effeminate-Lusty	0.00	0.08	0.36	0.32	0.24	1	0.0526	3.72
d_{21}	Light-Heavy	0.12	0.20	0.44	0.24	0.00	1	0.0550	2.80
d_2	Slim-Bulgy	0.00	0.08	0.20	0.36	0.36	1	0.0550	4.00
d_8	Non-streamline-Streamline	0.12	0.16	0.48	0.20	0.04	1	0.0616	2.88
d_{10}	Shrive-Fleshly	0.04	0.08	0.48	0.20	0.20	1	0.0654	3.44
d_{16}	Unbalanced-Harmonious	0.08	0.08	0.36	0.32	0.16	1	0.0750	3.40
d_{13}	Inelastic-Elastic	0.08	0.28	0.32	0.20	0.12	1	0.0800	3.00
d_1	Thin-Fat	0.08	0.08	0.28	0.36	0.20	1	0.0806	3.52
d_{20}	Lazy-Vivid	0.08	0.16	0.16	0.44	0.16	1	0.0854	3.44
d_3	Dented-Swollen	0.16	0.20	0.40	0.12	0.12	1	0.0884	2.84
d_9	Knotty-Smooth	0.12	0.20	0.24	0.32	0.12	1	0.0916	3.12
d_{15}	Cabinet-Huge	0.36	0.08	0.48	0.08	0.00	2	0.0676	2.28
d_5	Short-Tall	0.44	0.20	0.32	0.00	0.04	2	0.0700	2.00
d_7	Flat-Thick	0.20	0.04	0.56	0.16	0.04	2	0.0700	2.80
d_{22}	Unsexy-Sexy	0.32	0.24	0.32	0.08	0.04	2	0.0776	2.28
d_{04}	Atrophic-Forceful	0.00	0.24	0.24	0.20	0.32	2	0.0850	3.60
d_{14}	Deft-Awkward	0.20	0.12	0.36	0.24	0.08	2	0.0916	2.88
d_6	Narrow-Wide	0.36	0.20	0.32	0.04	0.08	2	0.0926	2.28
d_{17}	Unique-Normal	0.20	0.12	0.36	0.08	0.24	3	0.1224	3.04

Table 4-3: Rank of Sensory Descriptor for t_2 ("*Nature*")

Sensory Descriptor		Distribution					Performance		Relevancy
		R_1	R_2	R_3	R_4	R_5	V^1	V^2	GP^R
d_{22}	Unsexy-Sexy	0.00	0.00	0.04	0.16	0.80	1	0.0164	4.76
d_{16}	Unbalanced-Harmonious	0.00	0.04	0.24	0.40	0.32	1	0.0450	4.00
d_8	Non-streamline-Streamline	0.00	0.08	0.20	0.44	0.28	1	0.0496	3.92
d_9	Knotty-Smooth	0.04	0.04	0.08	0.40	0.44	1	0.0634	4.16
d_{10}	Shrive-Fleshly	0.00	0.12	0.20	0.24	0.44	1	0.0700	4.00
d_6	Narrow-Wide	0.16	0.20	0.48	0.08	0.08	1	0.0726	2.72
d_{12}	Fragility-Strong	0.08	0.20	0.40	0.20	0.12	1	0.0746	3.08
d_3	Dented-Swollen	0.08	0.12	0.20	0.28	0.32	1	0.0994	3.64
d_{19}	Sebaceous-Muscular	0.12	0.12	0.12	0.36	0.28	1	0.1104	3.56
d_{21}	Light-Heavy	0.20	0.08	0.52	0.20	0.00	2	0.0626	2.72
d_4	Atrophic-Forceful	0.04	0.08	0.04	0.44	0.40	2	0.0696	4.08
d_5	Short-Tall	0.08	0.04	0.28	0.44	0.16	2	0.0704	3.56
d_7	Flat-Thick	0.04	0.28	0.24	0.20	0.24	2	0.0936	3.32
d_{11}	Effeminate-Lusty	0.08	0.32	0.28	0.12	0.20	2	0.0974	3.04
d_1	Thin-Fat	0.08	0.08	0.04	0.28	0.52	2	0.0996	4.08
d_{13}	Inelastic-Elastic	0.08	0.28	0.20	0.24	0.20	2	0.1000	3.20
d_{18}	Unstylish-Stylish	0.08	0.08	0.00	0.24	0.60	2	0.1000	4.20
d_{20}	Lazy-Vivid	0.08	0.28	0.24	0.16	0.24	2	0.1050	3.20
d_{15}	Cabinet-Huge	0.24	0.12	0.20	0.36	0.08	2	0.1096	2.92
d_{17}	Unique-Normal	0.16	0.00	0.12	0.40	0.32	2	0.1126	3.72
d_{14}	Deft-Awkward	0.24	0.20	0.08	0.32	0.16	2	0.1324	2.96
d_2	Slim-Bulgy	0.16	0.04	0.08	0.20	0.52	2	0.1366	3.88

Table 4-4: Rank of Sensory Descriptor for t_3 (“*Attractive*”)

Tables 4-2, 4-3, and 4-4 present the distributions of the relations between the 3 involved fashion themes and all the 22 sensory descriptors. The sensory descriptors are ranked according to their performance values. In each of these tables, if a sensory descriptor is highly ranked, its performance is better and the perceptions of all the consumers are conform to each other. Otherwise, its performance is worse and the perceptions of the consumers are diversified. For instance, Figure 4-6 compares the performances of fashion theme t_1 ("*Sporty*") related to d_{12} ("*Fragile-Strong*") and d_{20} ("*Lazy-Vivid*"). The distribution of d_{12} covers R_2, R_3, R_4 and R_5 while that of d_{20} from R_1 to R_5. Obviously, the distribution of d_{12} is more concentrated than that of d_{20}, meaning that its performance is better than the distribution of d_{20}.

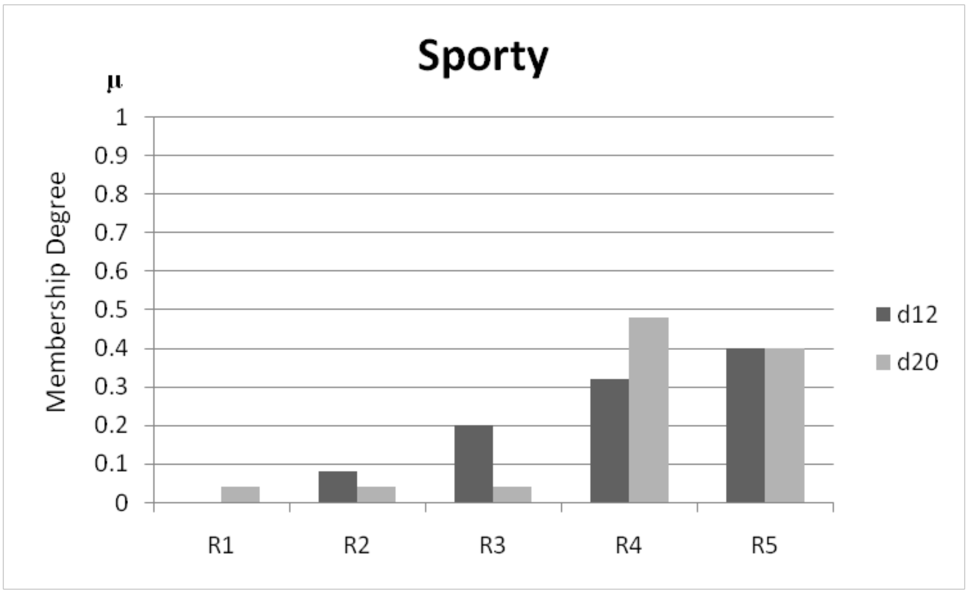


Figure 4-6: Comparison between d_{12}("*Fragile-Strong*") and d_{20}("*Lazy-Vivid*") for t_1("*Sporty*")

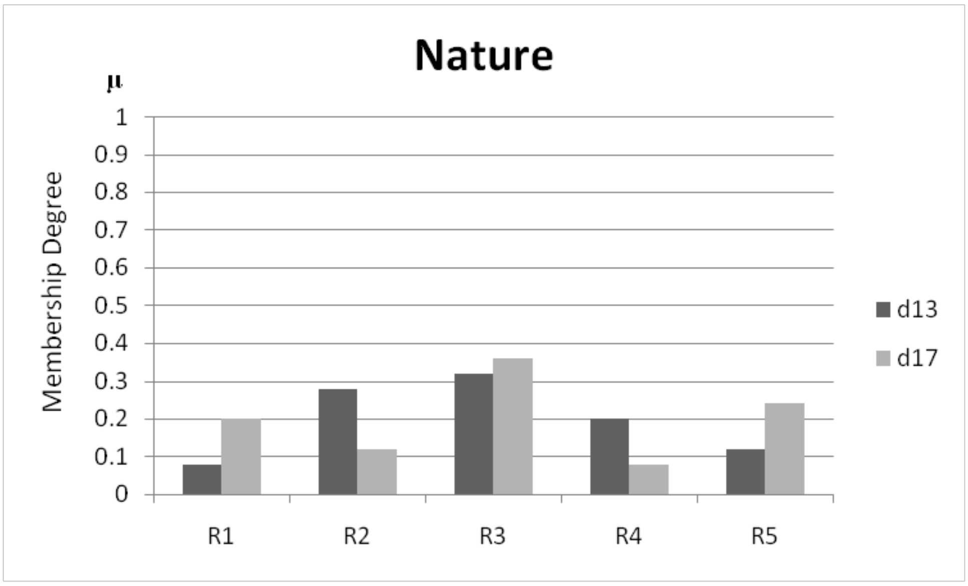


Figure 4-7: Comparison between d_{13}(“*Inelastic-Elastic*”) and d_{17}(“*Unique-Normal*”) for t_2(“*Nature*”)

In Figure 4-7, the performances of d_{13}(“*Inelastic-Elastic*”) and d_{17}(“*Unique-Normal*”) related to t_2 (“*Nature*”) are similar. However, according to Table 4-3, d_{17} is more relevant than d_{13} related to t_2. In fact, the performance criteria have defined differently from the relevancy criterion.

Dissimilarity		
t_1 and t_2	t_2 and t_3	t_1 and t_3
0.1120	0.1535	0.1338

Table 4-5: Dissimilarity of Fashion Theme

The dissimilarity values of the three involved fashion themes are presented in Table 4-5. The dissimilarity between t_1 and t_2 is the smallest, meaning that they are close at consumer perception level. t_2 is very different from t_3 for consumers.

4.2.3 Relation between Body Ratios (Naked Body) and a Fashion Theme

According to the result of Section 4.2, we obtain the fuzzy relation between the fashion theme t_i and the sensory descriptors of D as follows.

$$REL(t_i, D) = \begin{bmatrix} \mu_{i1}(R_1) & \cdots & \mu_{i1}(R_5) \\ \vdots & \ddots & \vdots \\ \mu_{im}(R_1) & \cdots & \mu_{im}(R_5) \end{bmatrix}$$

Also, according to Section 4.3, we obtain the fuzzy relation between these sensory descriptors and the body ratios of a specific body Y as follows.

$$REL(D, BR^Y) = \begin{bmatrix} \mu_1^Y(C_1) & \cdots & \mu_1^Y(C_9) \\ \vdots & \ddots & \vdots \\ \mu_m^Y(C_1) & \cdots & \mu_m^Y(C_9) \end{bmatrix}$$

The combination of the two above fuzzy relations $REL(t_i, D)$ and $REL(D, BR^Y)$, can be used to analyze the relevancy of a body shape Y related to the fashion theme t_i. Formally, this relevancy degree is defined by

$$REL(t_i, BR^Y) = REL(t_i, D) \circ REL(D, BR^Y)^T = \begin{bmatrix} \mu_i^Y(R_1, C_1) & \cdots & \mu_i^Y(R_1, C_9) \\ \vdots & \ddots & \vdots \\ \mu_i^Y(R_5, C_1) & \cdots & \mu_i^Y(R_5, C_9) \end{bmatrix}$$

where "∘" is the composition operation of two fuzzy relations.

$REL(t_i, BR^Y)$ is a (5×9) dimensional matrix which represents the fuzzy relation between the fashion theme t_i and the special body shape Y.

4.3 Model II: Characterization of the Relevancy of Body Ratios (with Garment Design) to a Fashion Theme

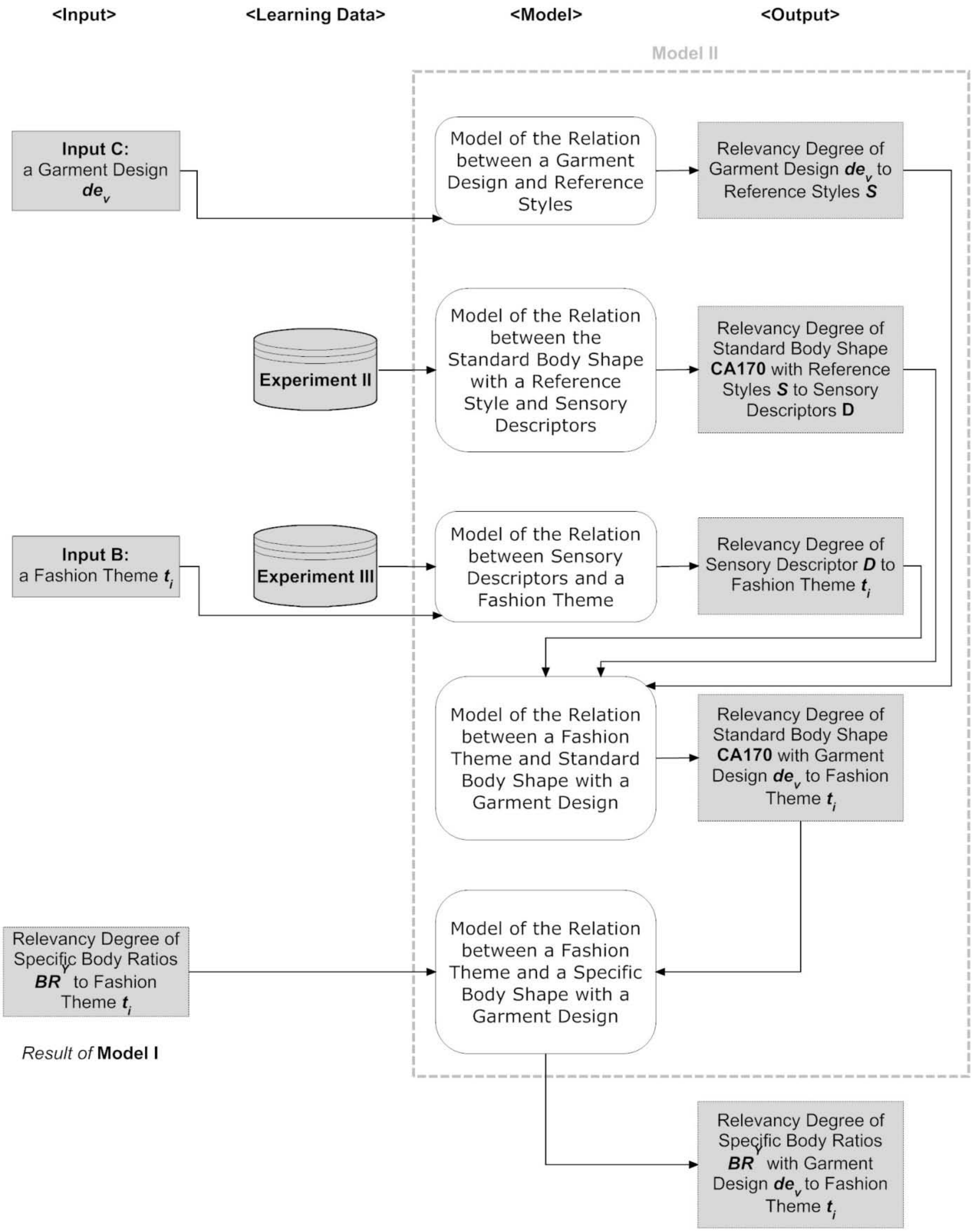


Figure 4-8: Functional Structure of **Model II**

The data flow of **Model II** is presented by its functional structure in Figure 4-8. The details of modeling for each component are given in the following sections.

4.3.1 Relation between a Garment Design and Reference Styles

In a design process, fashion designers create a new fashion product using two approaches. In the first approach, people view the new style as complete or partial revival of an existing reference style. In the second approach, a new style is generated inspired by several different reference styles. In this context, we use the relevancy degrees of the reference styles to express a new garment design. In my project, for simplicity, all the new garment designs are created by controlling the five reference styles, i.e. “Chester”, “Ulster”, “Balmacaan”, “Trench” and “Duffle”.

Therefore, the relation between a new garment design $de_υ$ and the reference styles S can be presented by

$$REL(de_{\upsilon}, S) = \left\{\left(s_1, L(s_1)\right), \dots, \left(s_{\xi}, L\left(s_{\xi}\right)\right)\right\}$$

where L is the linguistic relevancy degrees of the garment design $de_υ$ related to the previous five reference styles, expressed by $\{L_1, L_2, L_3, L_4, L_5\}$. The relevancy degrees take values from {“Not belong to”, “a little belong to”, “Belong to”, “Fairly belong to”, “Totally belong to”} with ($\xi = 5$).

$REL(de_{\upsilon}, S)$ can also be rewritten by

$$REL(de_{\upsilon}, S) = \left\{(s_1, eq[L(s_1)]), \dots, \left(s_{\xi}, eq\left[L\left(s_{\xi}\right)\right]\right)\right\}$$

$eq[L(s_{\lambda})]$ $(\lambda \in \{1, 2, \dots, \xi\})$ is the equivalent value of $L(s_{\lambda})$. Therefore, the linguistic set $\{L_1, L_2, L_3, L_4, L_5\}$ can be replaced by $\{0, 0.25, 0.5, 0.75, 1\}$.

4.3.2 Relation between the Standard Body with a Reference Style and Sensory Descriptors

From the sensory evaluation of the virtual male body shapes with design style (Experiment II in Chapter 2), the relation between a reference style and the sensory descriptors can be extracted for determining how each reference style can change the image of the standard body shape (CA170) related to the sensory descriptors. For example, a duffel-style overcoat can make the male wearer of standard body shape more vivid. In Experiment II, only fashion experts give their evaluations according to their experience.

Similar to the sensory evaluation of the virtual body shapes, for an expert e_i, the evaluation score of a standard body shape with a specific reference style s_λ related to a sensory descriptor d_j also takes on value of the linguistic set $\{C_1, C_2, \dots, C_9\}$. Furthermore, the evaluation results from r expert are aggregated by the same way in section 4.3 as follows.

$$REL(s_\lambda, d_j) = \left(\frac{NB_{kj}(C_1)}{r}\ \frac{NB_{kj}(C_2)}{r} \dots \frac{NB_{ij}(C_9)}{r}\right) = \{\mu_{kj}(C_1), \mu_{kj}(C_2), \dots, \mu_{kj}(C_9)\}$$

where $NB(C_k)$ is the number of evaluators selecting the linguistic value C_k from the result of the sensory evaluation. Evidently, the sum of all components in $REL(s_\lambda, d_j)$ is 1.

Then, the relation between the classical style s_λ and all the m sensory descriptors D can be represented by

$$\begin{aligned} REL(D, s_\lambda) &= (REL(t_i, d_1)^T\ REL(t_i, d_2)^T\ \dots\ REL(t_i, d_m)^T)^T \\ &= \begin{bmatrix} \mu_{k1}(C_1) & \cdots & \mu_{k1}(C_9) \\ \vdots & \ddots & \vdots \\ \mu_{km}(C_1) & \cdots & \mu_{km}(C_9) \end{bmatrix} \end{aligned}$$

where $REL(D, s_\lambda)$ is a $(m \times 9)$ dimensional fuzzy relation matrix.

4.3.3 Relation between a Fashion Theme and the Standard Body Shape with a New Garment Design

The relation between a fashion theme t_i and the standard body shape with a new garment design de_v shows that how this garment design change the image of this body shape for t_i.

As a garment design is usually composed of several reference styles, we first evaluate the relations between t_i and the standard body shape with all the reference styles and then aggregate these relations using fuzzy composition operation. The operations are as in the follows.

The relation between the fashion theme $\mathrm{t_i}$ and all the sensory descriptors of D in Section 4.2 is represented by

$$REL(t_i, D) = \begin{bmatrix} \mu_{i1}(R_1) & \cdots & \mu_{i1}(R_5) \\ \vdots & \ddots & \vdots \\ \mu_{im}(R_1) & \cdots & \mu_{im}(R_5) \end{bmatrix}$$

The relationship between the standard body shape with a reference style s_λ and all the m sensory descriptors of D in Section 4.6 is represented by

$$REL(D, s_\lambda) = \begin{bmatrix} \mu_{k1}(C_1) & \cdots & \mu_{k1}(C_9) \\ \vdots & \ddots & \vdots \\ \mu_{km}(C_1) & \cdots & \mu_{km}(C_9) \end{bmatrix}$$

The relationship between the fashion theme $\mathrm{t_i}$ and the standard body shape with a the style $\mathrm{s_\lambda}$ is calculated by

$$REL(t_i, S_\lambda) = REL(t_i, D) \circ REL(D, s_\lambda)^T$$

It is a (5×9)-dimensional fuzzy matrix. The sign "∘" is the Max-Min composition between the two fuzzy relations.

Next, the relation between a new garment design de_v and all the reference styles of S (see Section 4.5) can be represented by

$$REL(de_v, S) = \{(s_1, eq[L(s_1)]), \dots, (s_\xi, eq[L(s_\xi)])\}$$

Thus the value $eq[L(s_\lambda)]$ can be considered as a weight for the relationship between the fashion theme t_i and a reference style s_λ.

The weighted relationship between t_i and s_λ can be calculated by the scalar multiplication [LEE, 2005] of the fuzzy matrix $REL(t_i, S_\lambda)$ and the weight $eq[L(s_\lambda)]$, which is expressed by

$$\begin{aligned}
\overline{\overline{REL}}(t_i, s_\lambda) &= eq[L(s_\lambda)] \cdot REL(de_\upsilon, S) \\
&= \begin{bmatrix} eq[L(s_\lambda)] \cdot \mu_{11}(t_i, S_\lambda) & \cdots & eq[L(s_\lambda)] \cdot \mu_{19}(t_i, S_\lambda) \\ \vdots & \ddots & \vdots \\ eq[L(s_\lambda)] \cdot \mu_{51}(t_i, S_\lambda) & \cdots & eq[L(s_\lambda)] \cdot \mu_{59}(t_i, S_\lambda) \end{bmatrix} \\
&= \begin{bmatrix} \overline{\overline{\mu_{11}}}(t_i, S_\lambda) & \cdots & \overline{\overline{\mu_{19}}}(t_i, S_\lambda) \\ \vdots & \ddots & \vdots \\ \overline{\overline{\mu_{51}}}(t_i, S_\lambda) & \cdots & \overline{\overline{\mu_{59}}}(t_i, S_\lambda) \end{bmatrix}
\end{aligned}$$

Finally, the fuzzy relation between the fashion theme t_i and the standard body shape with the new garment design de_υ is defined by

$$\begin{aligned}
REL(t_i, de_\upsilon) &= \bigcup_{\lambda=1}^{\xi} \overline{\overline{REL}}(t_i, s_\lambda) \\
&= \begin{bmatrix} \bigvee_\lambda [\overline{\overline{\mu_{11}}}(t_i, S_\lambda)] & \cdots & \bigvee_\lambda [\overline{\overline{\mu_{19}}}(t_i, S_\lambda)] \\ \vdots & \ddots & \vdots \\ \bigvee_\lambda [\overline{\overline{\mu_{51}}}(t_i, S_\lambda)] & \cdots & \bigvee_\lambda [\overline{\overline{\mu_{59}}}(t_i, S_\lambda)] \end{bmatrix} \\
&= \begin{bmatrix} \underset{\lambda}{Max}\{\overline{\overline{\mu_{11}}}(t_i, S_\lambda)\} & \cdots & \underset{\lambda}{Max}\{\overline{\overline{\mu_{19}}}(t_i, S_\lambda)\} \\ \vdots & \ddots & \vdots \\ \underset{\lambda}{Max}\{\overline{\overline{\mu_{51}}}(t_i, S_\lambda)\} & \cdots & \underset{\lambda}{Max}\{\overline{\overline{\mu_{59}}}(t_i, S_\lambda)\} \end{bmatrix}
\end{aligned}$$

which is also (5×9)-dimensional fuzzy matrix.

4.3.4 Relation between a Fashion Theme and a Special Body Shape with a Garment Design

The fuzzy matrix $REL(t_i, BR^Y)$, obtained in Section 4.2, can be used to characterize the relation of the fashion theme ti and a special body shape Y. In the same way, the fuzzy matrix $REL(t_i, de_\xi)$ can be used to characterize the relation of t_i and the standard body shape with the garment design de_{ξ}.

The relation between the fashion theme t_i and the special body shape Y with the garment design de_{ξ}, can be calculated by using the fuzzy union operation (Maximum operator) of the above two fuzzy relation matrix.

$$REL\left(t_i, BR^Y \vee de_{\xi}\right)$$

$$= \begin{bmatrix} Max\{\mu_{11}(t_i, BR^Y), \mu_{11}\left(t_i, de_{\xi}\right)\} & \cdots & Max\{\mu_{11}(t_i, BR^Y), \mu_{19}\left(t_i, de_{\xi}\right)\} \\ \vdots & \ddots & \vdots \\ Max\{\mu_{51}(t_i, BR^Y), \mu_{11}\left(t_i, de_{\xi}\right)\} & \cdots & Max\{\mu_{11}(t_i, BR^Y), \mu_{59}\left(t_i, de_{\xi}\right)\} \end{bmatrix}$$

This relation is represented by the (5×9)-dimensional fuzzy matrix $REL\left(t_i, BR^Y \vee de_{\xi}\right)$, which can be analyzed by using the criteria of gravity center and projections of $REL(t_i, BR^Y)$ defined previously.

All the models given in this chapter will be organized together to form the fashion design support system, mentioned in Chapter 1. These models have been illustrated, analyzed and validated through a series of real design examples. The corresponding results will be shown in Chapter 5.

Chapter 5 Fashion Design Support System through Two Case Studies

This chapter is composed of two parts. In the first part, the learning data acquired from the three experiments of Chapter 2 and the models developed in Chapter 4 are organized together to form a fashion design support system. In the second part, the proposed decision support system is illustrated through two real examples of designing styles of male overcoats. The results of this application are analyzed at the end of this chapter.

5.1 Architecture of the Design Support System

According to the principles of the garment design support system proposed in Chapter 1, the perceptual data from both design experts and consumers, obtained from the experiments, will be taken as learning data of the decision support unit inside the system. This decision support unit permits to determine from a series of computations whether a specific body shape is conform to a given fashion theme. The three perception databases are connected to the different stages of this decision support unit (see Figure 5-1). Furthermore, the special body shape, represented by its body ratios BR^Y(Input **A**), the required fashion theme t_i (Input **B**), and the new garment design de_v (Input **C**), obtained by combining different reference styles, are the three input components of the decision support unit.

The first stage of the decision support unit is **Model I**, whose aim is to evaluate the relevancy of a specific naked body shape Y, expressed by body ratios BR^Y, related to a required fashion theme t_i. The second stage of the decision support unit is **Model II**, whose aim is to evaluate the relevancy of a specific body Y with a garment design style de_v related to t_i. In the last stage of the decision support unit, the previous two relevancy results are compared using a gravity center-based criterion in order to evaluate whether the new garment design de_v is suitable for the body shape Y in terms of image improvement related to the fashion theme t_i.

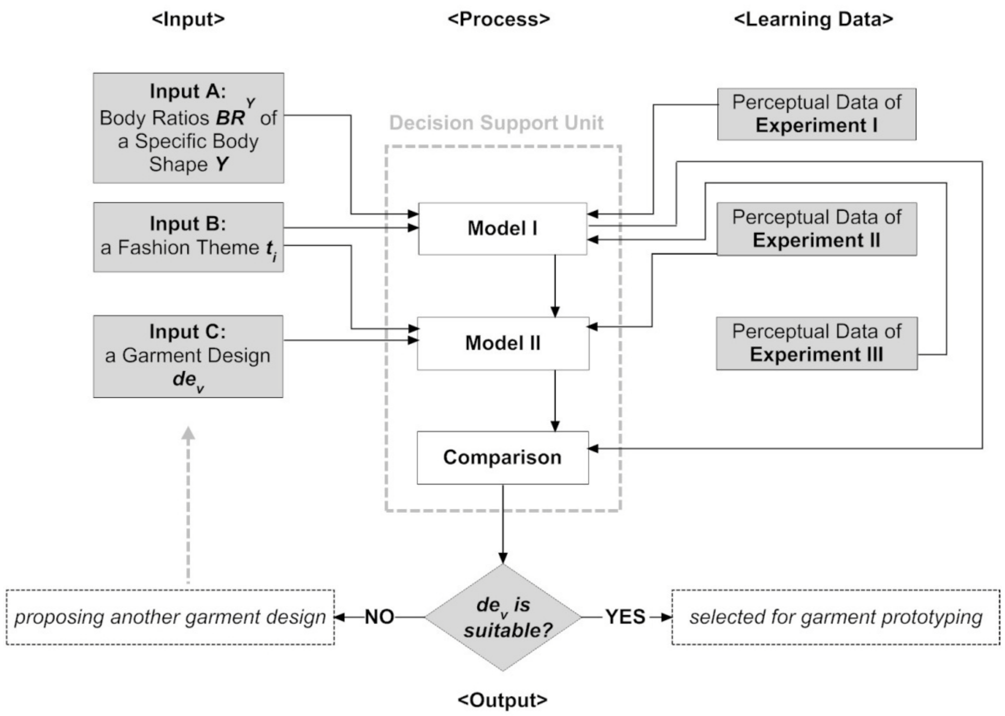


Figure 5-1: The Proposed Fashion Design Support System

From the functional points of view, the three stages of the decision support unit can be summarized as follows.

1) Stage 1 of Decision Support Unit: Model I

The details of **Model I** (Figure 4-1) have been presented in Chapter 4 (Section 4-2). It is set up by learning from the design expert's perceptual data and the consumer's perceptual data. A (5×9)-dimensional fuzzy matrix $REL(t_i, BR^Y)$ is generated to represent the relevancy degree of the special body ratios BR^Y to the fashion theme t_i.

2) Stage 2 of Decision Support Unit: Model II

The details of **Model II** (Figure 4-8) have also been given in Chapter 4 (Section 4-3). It is set up by learning from the perceptual data obtained from Experiment II and Experiment III. The relevancy degree of the special body ratios BR^Y with the garment design de_v to the fashion theme t_i is represented by another (5×9) -dimensional fuzzy matrix, $REL(t_i, BR^Y \vee de_v)$.

3) Stage 3 of Decision Support Unit: Comparison

The aim of this stage is to determine whether the garment design de_v is feasible for the special body ratios for promoting the relevancy of the fashion theme t_i.

For this propose, we propose a criterion based on the principle of gravity center.

For computing the gravity center of the fuzzy matrix $REL(t_i, BR^Y)$, we first transform the linguistic values $\{R_1, R_2, R_3, R_4, R_5\}$ into the equivalent numeric values $\{0, 0.25, 0.5, 0.75, 1\}$ and $\{C_1, C_2, C_3, C_4, C_5, C_6, C_7, C_8, C_9\}$ into $\{-1, -0.75, -0.5, -0.25, 0, 0.25, 0.5, 0.75, 1\}$.

The gravity of the fuzzy relation matrix (see example in Figure 5-2-b)

$$REL(t_i, BR^Y) = \begin{bmatrix} \mu_i^Y(R_1, C_1) & \cdots & \mu_i^Y(R_1, C_9) \\ \vdots & \ddots & \vdots \\ \mu_i^Y(R_5, C_1) & \cdots & \mu_i^Y(R_5, C_9) \end{bmatrix}$$

is calculated by

$$G\_REL(t_i, BR^Y) = \sum_{j=1}^{5} \sum_{k=1}^{9} \mu_{jk}\, eq(R_j) eq(C_k)$$

where $eq(R_j)$ and $eq(C_k)$ are the equivalence values of R_j and C_k respectively.

The projection of the gravity center on the axis Y is calculated by

$$GP^Y\_REL(t_i, BR^Y) = G\_REL(t_i, BR^Y) \,/\, \sum_{j=1}^{5} \sum_{k=1}^{9} \mu_{jk}\;\; eq(R_j)$$

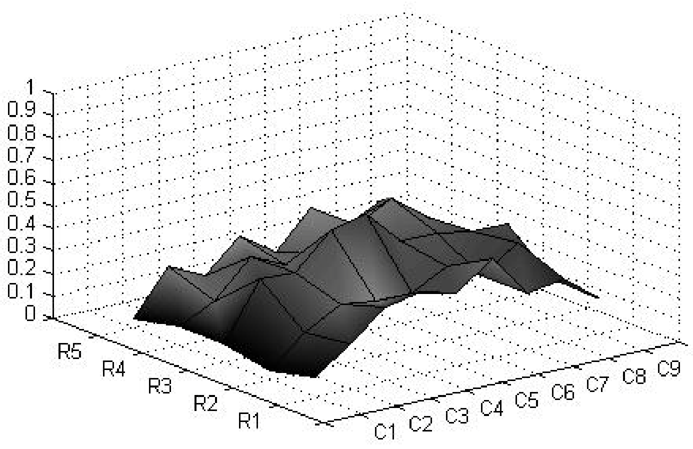
Similarly, The projection of the gravity center on the axis t_i is calculated by

$$GP^{t_i}\_REL(t_i, BR^Y) = G\_REL(t_i, BR^Y) \,/\, \sum_{j=1}^{5} \sum_{k=1}^{9} \mu_{jk}\;\; eq(C_k)$$

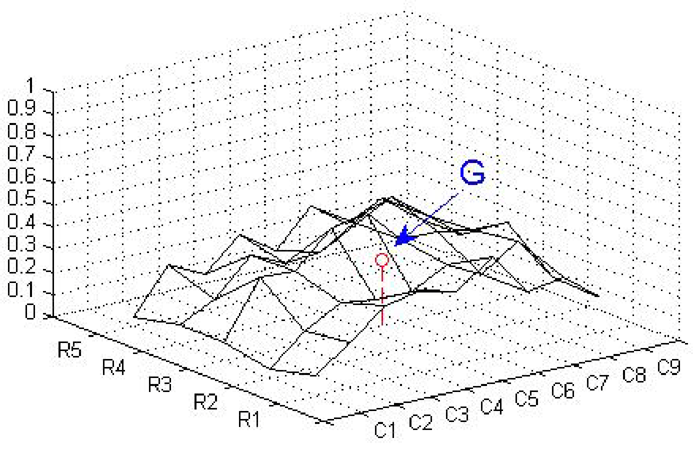
The combination of these two projections (see example in Figure 5-2-c) is:

$GP^{Y \times t_i}\_REL(t_i, BR^Y) = (\alpha^i, \beta^i)$

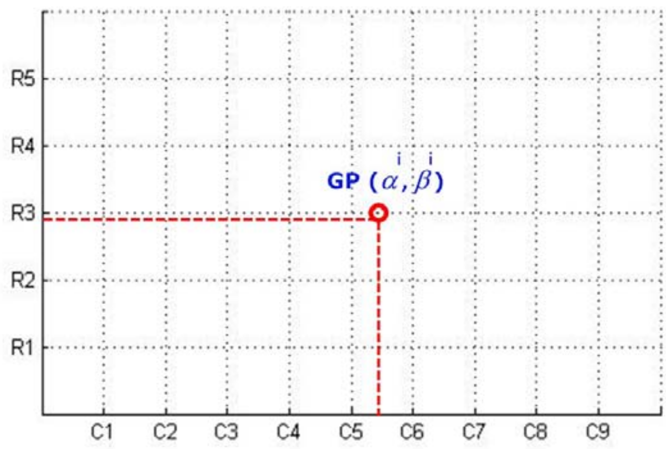
where $\alpha^i = GP^Y\_REL(t_i, BR^Y)$ and $\beta^i = GP^{t_i}\_REL(t_i, BR^Y)$.



(a) Distribution of a fuzzy relation matrix



(b) Gravity center of the distribution



(c) Projection of the gravity center on the $(Y \times t_i)$ plan

Figure 5-2: Distribution, Gravity Center and Projection of a Fuzzy Relation Matrix

The product of the two projection $GP^Y\_REL(t_i, BR^Y)$ and $GP^{t_i}\_REL(t_i, BR^Y)$ is defined by

$$\omega^i = \alpha^i \cdot \beta^i$$

For the fuzzy matrix $REL(t_i, BR^Y \vee de_v)$, the computation of its gravity center and its projections are the same as those of $REL(t_i, BR^Y)$. Similarly, we use $\overline{\overline{\alpha_v^i}}$ to denote the projection $GP^Y\_REL(t_i, BR^Y)$ and $\overline{\overline{\beta_v^i}}$ the projection $GP^{t_i}\_REL(t_i, BR^Y \vee de_v)$ of the gravity center $GP^{Y \times t_i}\_REL(t_i, BR^Y \vee de_v)$. Their product is expressed by $\overline{\overline{\omega_v^i}}$.

Moreover, we also define the difference of the projections by

$$\Delta\alpha_v^i = \overline{\overline{\alpha_v^i}} - \alpha^i$$

$$\Delta\beta_v^i = \overline{\overline{\beta_v^i}} - \beta^i$$

And the difference of the products is

$$\Delta\omega_v^i = \overline{\overline{\omega_v^i}} - \omega^i$$

For comparison and analysis of the two relevancy degrees obtained from **Model 1** and **Model 2**, we define the following rules (see Figure 5-3):

a-1) For the value of α (α^i or $\overline{\overline{\alpha_v^i}}$):

Bigger is α , higher is the relevancy degree of the special body ratios (naked or with garment design) to the fashion theme t_i for the design expert perception. Otherwise, the relevancy degree is lower.

a-2) For the value of β (β^i or $\overline{\overline{\beta_v^i}}$):

Bigger isβ , higher is the relevancy degree of the special body ratios (naked or with garment design) to the fashion theme t_i for the consumer perception. Otherwise, the relevancy degree is lower.

a-3) For the value of ω (ω^i or $\overline{\overline{\omega_v^i}}$):

Bigger is ω , higher is the relevancy degree of the special body ratios (naked or with garment design) to the fashion theme t_i for the compromise between design expert perception and consumer perception. Otherwise, the relevancy degree is lower.

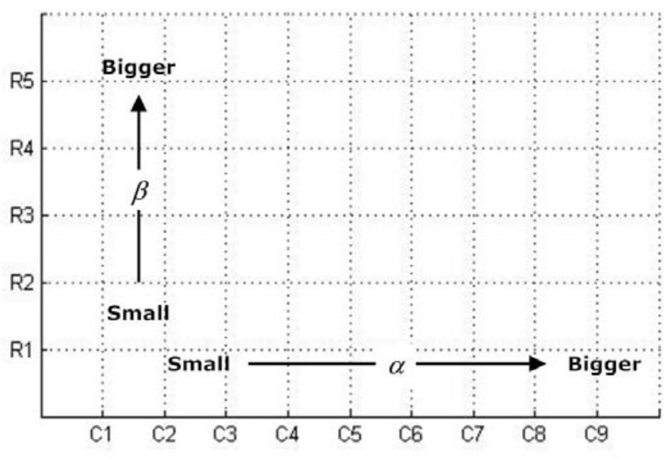


Figure 5-3: Illustration of Rules a-1), a-2) and a-3)

The rules a-1), a-2), a-3) are used to quantitatively characterize the relevancy degrees of a specific body shape to different perceptions. Next, we combine these rules, which can be used in more general cases.

For the gravity center of the fuzzy relation matrix (see Figure 5-4):

b-1) If $\alpha > eq(C_5)$ (i.e. 5) and $\beta > eq(R_3)$ (i.e. 3), then the special body ratios (naked or with garment design) is relevant to the fashion theme t_i for the compromise between expert perception and consumer perception;

b-2) If $\alpha \leq eq(C_5)$ and $\beta > eq(R_3)$, then the special body ratios (naked or with garment design) is irrelevant to the fashion theme t_i for the expert perception and relevant for the consumer perception;

b-3) If $\alpha > eq(C_5)$ and $\beta \leq eq(R_3)$, then the special body ratios (naked or with garment design) is relevant to the fashion theme t_i for the expert perception and irrelevant for the consumer perception;

b-4) If $\alpha \leq eq(C_5)$ and $\beta \leq eq(R_3)$, then the special body ratios (naked or with garment design) is irrelevant to the fashion theme t_i for both the expert perception and the consumer perception.

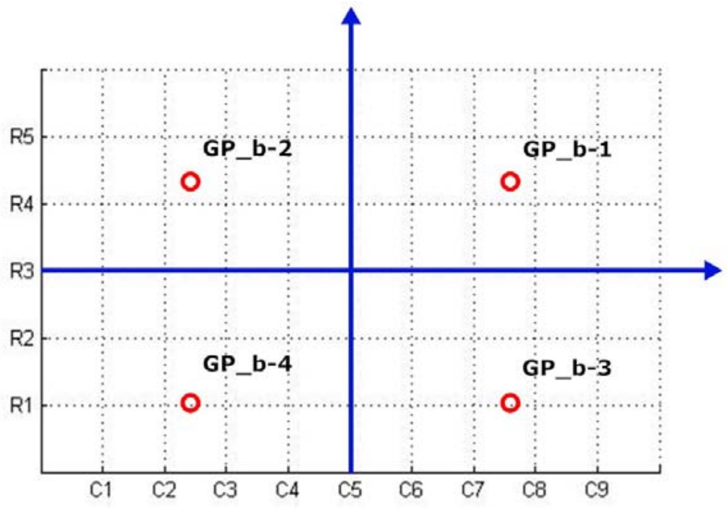


Figure 5-4: Illustration of Rules b-1), b-2), b-3) and b-4)

For measure the change of the fuzzy relation matrix from the naked body ratios to the one with a garment design style. The values of change will be measure by the following rules, which are still based on the rules (a-1), (a-2), (a-3):

c-1) For the value of $\Delta\alpha_v^i$:

If $\Delta\alpha_v^i$ is a positive value, the relevancy degree of the body shape Y with the garment design de_v to the fashion theme t_i is higher than that of the naked body shape Y for the expert perception;

If $\Delta\alpha_v^i$ is 0, there is no difference;

If $\Delta\alpha_v^i$ is a negative value, the relevancy degree of the body shape Y with the garment design de_v to the fashion theme t_i is smaller than that of the naked body shape Y for the expert perception.

c-2) For the value of $\Delta\beta_v^i$:

If $\Delta\beta^v$ is a positive value, the relevancy degree of the body shape Y with the garment design de_v to the fashion theme t_i is higher than that of the naked body shape Y for the consumer perception;

If $\Delta\beta_v^i$ is 0, there is no difference;

If $\Delta\beta_v^i$ is a negative value, the relevancy degree of the body shape Y with the garment design de_v to the fashion theme t_i is smaller than that of the naked body shape Y based on consumer perception.

c-3) For the value of $\Delta\omega_v^i$:

If $\Delta\omega_v^i$ is a positive value, the relevancy degree of the body shape Y with the garment design de_v to the fashion theme t_i is higher than that of the naked body shape Y for the compromise between the expert perception and the consumer perception;

If $\Delta\omega_v^i$ is 0, there is no difference;

If $\Delta\omega_v^i$ is a negative value, the relevancy degree of the body shape Y with the garment design de_v to the fashion theme t_i is smaller than that of the naked body shape Y for the compromise between the expert perception and the consumer perception.

According to the previous rules of comparison and analysis, we define the evaluation criterion of new garment design styles as follows.

If the value of $\Delta\omega_v^i$ is positive, the garment design style de_v will be selected as a feasible design style for promoting the relevancy of the body shape Y to the fashion theme t_i; otherwise, design style de_v will be rejected.

5.2 Case Studies: Application of the Design Support System

Two real cases are proposed for showing the effectiveness of the design support system. In the related experiments, the special body ratios are obtained from the body measurements taken on real consumers. The fashion themes are those provided by the marketing experts, i.e. "*Sporty*", "*Nature*", and "*Attractive*". In order to minimize the development cost, our design strategy is to create a series of new design styles by copying, modifying and combining five classical references of styles: "*Chester*", "*Ulster*", "*Balmacaan*", "*Trench*" and "*Duffle*".

5.2.1 Case Study I: Customized Design

In this section, the proposed fashion design support system is tested and validated by designing customized styles for different specific body shapes. The aim is to show, through the designed styles, the specificity of their body shapes in terms of a required fashion theme. This design strategy is more relevant to the market of high fashion (haute couture) on Internet.

1) Input:

a) **Target market**: Three different body shapes are selected from a database of body measurements, taken from young men of 25 to 35 years old in Eastern China. The corresponding data are given in Table 5-1:

		Special Body Shapes		
		$Y01$	$Y02$	$Y03$
Body Measurements				
b_1 (Stature):		169	171.5	162.5
b_2 (Arm Length):		53.5	54.5	49
b_3 (Chest Circumstance):		89.5	80	84.6
b_4 (Neck Circumstance):		37	36	36.5
b_5 (Waist Circumstance):		76.5	65	68.8
b_6 (Hip Circumstance):		94	87	86.1
				Unit: cm
Body Ratios				
$br_1 \rightarrow$	br_2/br_1:	0.3166	0.3178	0.3015
$br_2 \rightarrow$	br_3 / br_1:	0.5296	0.4665	0.5206
$br_3 \rightarrow$	br_4 / br_1:	0.2189	0.2099	0.2246
$br_4 \rightarrow$	br_5 / br_1:	0.4527	0.3790	0.4234
$br_5 \rightarrow$	br_6 / br_1:	0.5562	0.5073	0.5298
$br_6 \rightarrow$	br_2 / br_3:	0.5978	0.6813	0.5792
$br_7 \rightarrow$	br_4 / br_3:	0.4134	0.4500	0.4314
$br_8 \rightarrow$	br_5 / br_3:	0.8547	0.8125	0.8132
$br_9 \rightarrow$	br_6 / br_3:	1.0503	1.0875	1.0177
$br_{10} \rightarrow$	br_5 / br_6:	0.8138	0.7471	0.7991
$br_{11} \rightarrow$	br_2 / br_4:	1.4459	1.5139	1.3425
$br_{12} \rightarrow$	br_2 / br_5:	0.6993	0.8385	0.7122
$br_{13} \rightarrow$	br_2 / br_6:	0.5691	0.6264	0.5691
$br_{14} \rightarrow$	br_4 / br_5:	0.4837	0.5538	0.5305
$br_{15} \rightarrow$	br_4 / br_6:	0.3936	0.4138	0.4239

Table 5-1: Body Measurements and Ratios in **Case Study I**

b) **Design objective**: promotion of the fashion themes: “*Attractive*” for male overcoats

c) **New garment styles**: These new styles in Figure 5-5 are described using their linguistic membership degrees related to five existing reference styles, “*Chester*”, “*Ulster*”, “*Balmacaan*”, “*Trench*” and “*Duffle*” (see Table 2-4 of Chapter 2). We have

de_1 de_2 de_3

Figure 5-5: New Garment Styles in **Case Study I**

de_1: Totally belong to *Chester*

de_2: Totally belong to *Duffle*

de_3: Fairly belong to *Chester* AND a little belong to *Ulster*

2) Stage 1 of Case Study I: Output of Model I

a) See Appendix 2-a for CART

b) See Appendix 2-b for Fuzzy-ID3

3) Stage 2 of Case Study I: Output of Model II

a) See Appendix 3-a for CART

b) See Appendix 3-b for FUZZY-ID3

4) Stage 3 of Case Study I: Comparison

a) For CART

Attractive (CART)
de_1

	$\Delta\omega_v^i$	Feasible or not?
Y01	0.6233	YES
Y02	1.4181	YES
Y03	0.6469	YES
	de_2	
	$\Delta\omega_v^i$	Feasible or not
Y01	0.0807	YES
Y02	0.2200	YES
Y03	0.2145	YES
	de_3	
	$\Delta\omega_v^i$	Feasible or not
Y01	-0.1079	NO
Y02	0.4294	YES
Y03	-0.1221	NO

Table 5-2: Results of CART for Y01, Y02, Y03 with the Garment Design Styles (de_1, de_2, de_3) Relevant to the Fashion Theme "*Attractive*"

b) Fuzzy-ID3

	Attractive (Fuzzy)	
	de_1	
	$\Delta\omega_v^i$	Feasible or not?
Y01	0.5206	YES
Y02	2.5990	YES
Y03	0.7446	YES
	de_2	
	$\Delta\omega_v^i$	Feasible or not
Y01	-0.2754	NO
Y02	0.3411	YES
Y03	-0.3937	NO
	de_3	

	$\Delta\omega_v^i$	Feasible or not
Y01	0.1489	YES
Y02	1.8507	YES
Y03	-0.0902	NO

Table 5-3: Results of FUZZY-ID3 for Y01, Y02, Y03 with the Garment Design Styles (de_1, de_2, de_3) Relevant to the Fashion Theme "*Attractive*"

The previous results show that given a specific design style and a fashion theme, the perceptual effects are different for different body shapes. It means that design strategy should be personalized. As shown in Table 5-3, two design styles, de_1 and de_3, are feasible for *Y01*. For Y02, all the three design styles are feasible. For Y03, only de_1 is feasible.

For a specific body shape, there exists some difference even for various feasible styles. For example, de1 and de3 are both feasible styles for Y01 but their relevancy degrees are different (0.52 for de1 and 0.15 for de3). The style de1 can be considered as the best recommendation. In practice, we just need to deliver both solutions to the designer who will make the final choice according to his/her personal experience.

5.2.2 Case Study II: Mass Market Selection

The purpose of this case is to apply our design support system to mass fashion market in order to select a set of feasible design styles meeting the needs of the market. Different from **Case I**, the personalized body shapes should be taken into account in the context of one population. This application is significant for developing new garment products with low costs.

1) Input

a) **Target market:** 60 special body shapes of male consumers whose ages vary from 25 to 35. Their body measurements are also taken from the database of the population in

Eastern China. The corresponding data are listed in Appendix 4.

b) **Design objective:** Promotion by combining the previous three fashion themes for the following objectives.

Objective 1: "*Sporty*" AND "*Nature*"

Objective 2: "*Sporty*" AND "*Attractive*"

Objective 3: "*Nature*" AND "*Attractive*"

c) **New design styles:** Six new garment design styles in Figure 5-6 are described using their linguistic membership degrees related to five existing reference styles, "*Chester*", "*Ulster*", "*Balmacaan*", "*Trench*" and "*Duffle*":

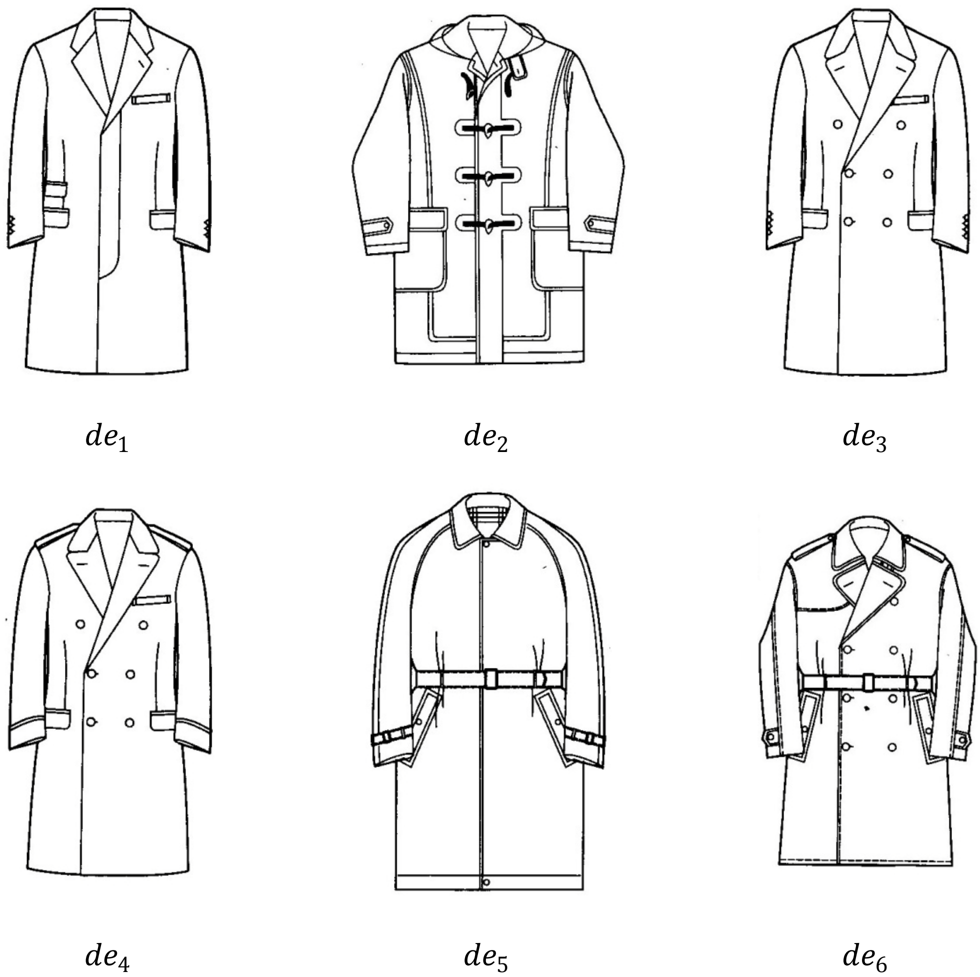


Figure 5-6: New Design Styles in **Case Study II**

de_1: Totally belong to *Chester*

de_2: Totally belong to *Duffle*

de_3: Fairly belong to *Chester* AND a little belong to *Ulster*

de_4: A little belong to *Chester* AND fairly belong to *Ulster*

de_5: Fairly belong to *Balmacaan* AND a little belong to *Trench*

de_6: A little belong to *Balmacaan* AND totally belong to *Trench*

2) Decision Output:

a) See Appendix 5-a for CART

b) See Appendix 5-b for FUZZY-ID3

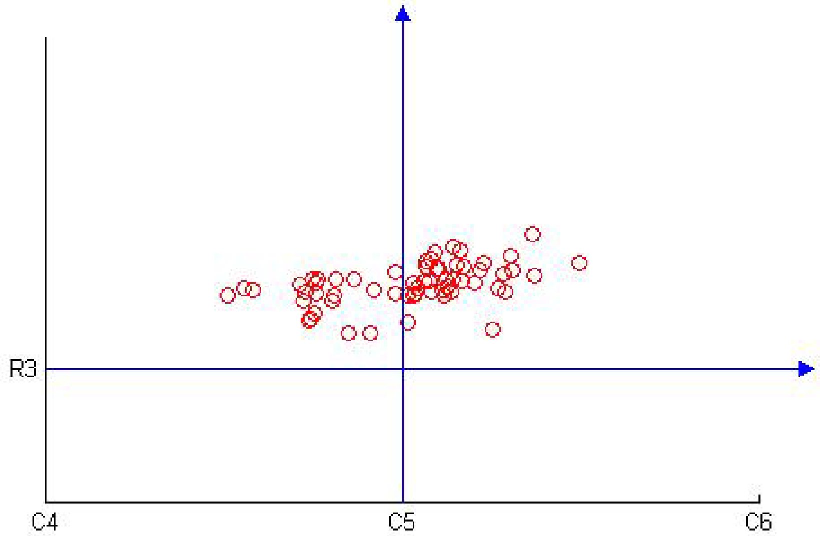


Figure 5-7: Relevancy degrees of the population (body ratios with de_2 for promoting "*Sporty*" by Fuzzy-ID3)

Having compared the relevancy degrees of **Model I** and **Model II**, we acquire 1080 solutions for each of CART and Fuzzy-ID3, deriving from the combinations of 60 body shapes, 6 design styles and 3 independent fashion themes ("*Sporty*", "*Nature*", and "*Attractive*"). For each fashion theme and each design style, we have 60 relevancy degrees, expressed by their fuzzy relation matrices. According to Section 5-1, the projections of their gravity centers (60 points) are distributed on the $(Y \times t_i)$ plan. One example is shown in Figure 5-7 for different cases. For each $(Y \times t_i)$ plan we can calculate the rate of feasible responses of these 60 body shapes for a given fashion theme and a given design style.

3) Rates of feasible responses for all the design styles

CART	de_1	de_2	de_3	de_4	de_5	de_6
Objective 1	68.33%	16.67%	16.67%	3.33%	1.67%	76.67%
Objective 2	85.00%	16.67%	28.33%	1.67%	0.00%	13.33%
Objective 3	71.67%	95.00%	18.33%	1.67%	0.00%	13.33%

Table 5-4: Rates of feasible responses for the design styles (CART)

Table 5-4 gives the rates of feasible responses of all the body shapes for each design style and each objective (CART). A feasible response is “YES” if and only if the corresponding evaluation criterion, defined previously, is positive (comparison between the naked body shape and the body shape with the given design style for a specific fashion theme). As each objective is composed of two fashion themes, a feasible response is “YES” if and only if the evaluation criteria are positive for both fashion themes. In any cases, higher is the evaluation criterion, more feasible the corresponding design style is to the design objective.

Based on the statistics of all the individual feasible responses, we define the following rules for selecting design styles for the whole population:

a) If the rate of feasible responses is equal to or more than 50%, the corresponding design style will be selected for the population.
b) The design style having the highest rate of feasible responses will be regarded as the best solution.

According to these rules, the result (CART) of selection is showed in Table 5-5 for each design objective.

CART	Feasible Selection	Best Selection
Objective 1	de_1, de_6	de_6
Objective 2	de_1	de_1
Objective 3	de_1, de_2	de_2

Table 5-5: Design styles selected (CART)

Also, we obtain the results for Fuzzy-ID3. Table 5-6 shows the corresponding rates of feasible responses for the design styles. And the selected design styles for the population are given in Table 5-7.

Fuzzy-ID3	de_1	de_2	de_3	de_4	de_5	de_6
Objective 1	53.33%	16.67%	53.33%	43.33%	40.00%	65.00%
Objective 2	68.33%	16.67%	63.33%	43.33%	31.67%	60.00%
Objective 3	53.33%	21.67%	53.33%	55.00%	31.67%	58.33%

Table 5-6: Rates of feasible responses for the design styles (Fuzzy-ID3)

Fuzzy-ID3	Feasible Selection	Best Selection
Objective 1	de_1, de_3, de_6	de_6
Objective 2	de_1, de_3, de_6	de_1
Objective 3	de_1, de_3, de_4, de_6	de_6

Table 5-7: Selected design styles for the population (Fuzzy-ID3)

5.2.3 Comparison of CART and Fuzzy-ID3

In these two cases, the results derived from the two algorithms, CART and Fuzzy-ID3, are quite similar in most aspects. However, some differences exist in distribution of the final relevancy degree (fuzzy relation matrix) and robustness of results.

1) Distribution of the relevancy degrees:

$Y01$; Naked; *Sporty* (CART)

REL	C1	C2	C3	C4	C5	C6	C7	C8	C9
R1	0.0000	0.1600	0.2000	0.2000	0.2800	0.4000	0.2800	0.1200	0.1600
R2	0.0000	0.2000	0.3801	0.5200	0.2800	0.2800	0.2400	0.2400	0.1200
R3	0.0000	0.2400	0.3200	0.3200	0.2514	0.3200	0.3200	0.2800	0.2983
R4	0.0000	0.3860	0.3200	0.3937	0.3600	0.4400	0.4400	0.3600	0.3600
R5	0.0000	0.4800	0.3672	0.5487	0.3582	0.5200	0.3600	0.2814	0.2000

$\alpha = 5.3005$

$\beta = 3.2579$

$\omega = 17.2688$

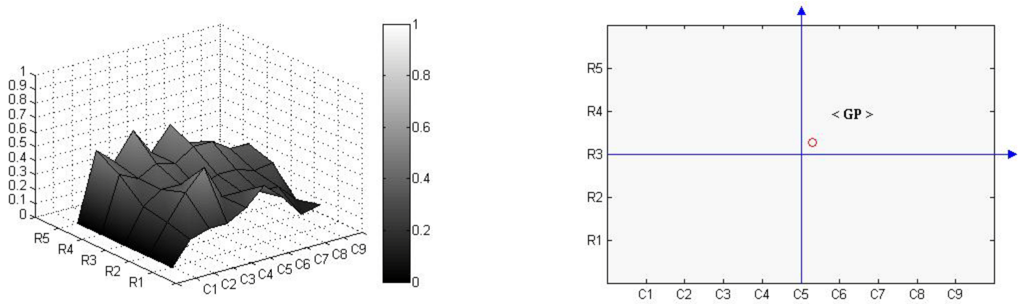


Table 5-8: Relevancy degree (CART) of Naked $Y01$ to "*Sporty*"

$Y01$; Naked; *Sporty* (MAL Fuzzy-ID3)

REL	C1	C2	C3	C4	C5	C6	C7	C8	C9
R1	0.0860	0.2000	0.2800	0.3000	0.3667	0.2800	0.1600	0.1600	0.1200
R2	0.0860	0.2473	0.2930	0.2800	0.2567	0.4400	0.2523	0.4227	0.1657
R3	0.0800	0.2400	0.2637	0.3117	0.3200	0.3200	0.3200	0.3030	0.1657
R4	0.0860	0.3333	0.2923	0.3743	0.3200	0.3600	0.4400	0.3267	0.2400
R5	0.0800	0.1600	0.3313	0.3003	0.3127	0.5377	0.4000	0.3330	0.3337

$\alpha = 5.4276$

$\beta = 3.2177$

$\omega = 16.3233$

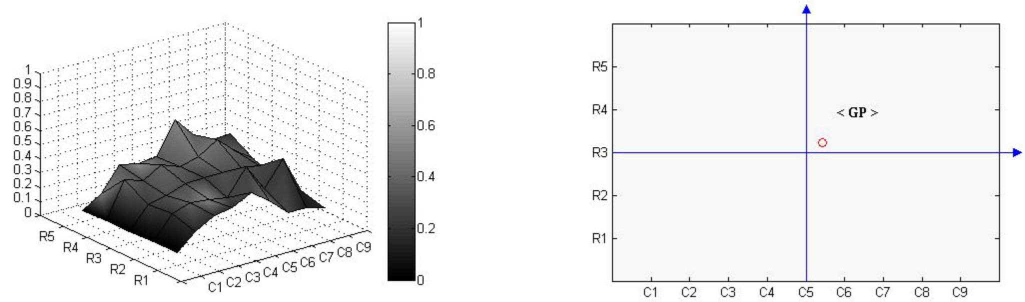
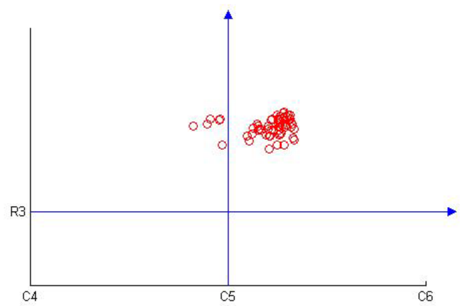


Table 5-9: Relevancy degree (Fuzzy-ID3) of Naked $Y01$ to "*Sporty*"

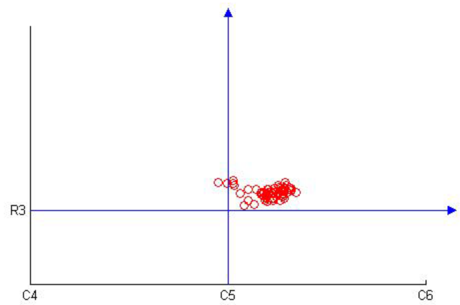
From Table 5-8 and Table 5-9, we can find that the results of CART are more rugged (more than one peaks with sharp forms). It means that the aggregation of the rules generated by CART from different experts is less consistent. The problem is related to inaccurate results generated by the binary splitting of the CART decision tree. The distribution of fuzzy-ID3 is more smooth and stable. It has better performance of treating missing data than CART.

2) Sensitivity of the results

Sporty



Nature



Attractive

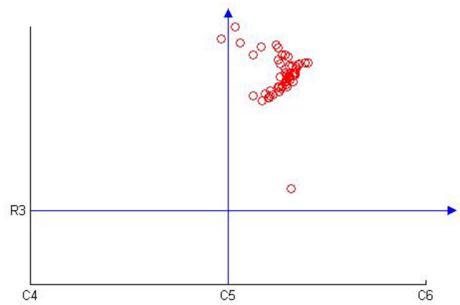
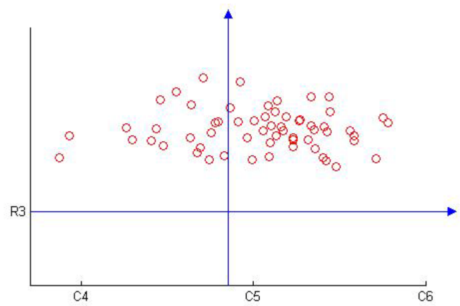
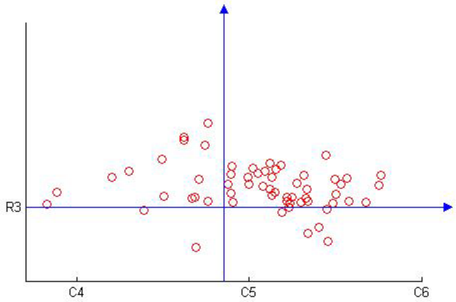


Figure 5-8: Distribution of relevancy degrees of the population for naked body shapes (CART)

Sporty



Nature



Attractive

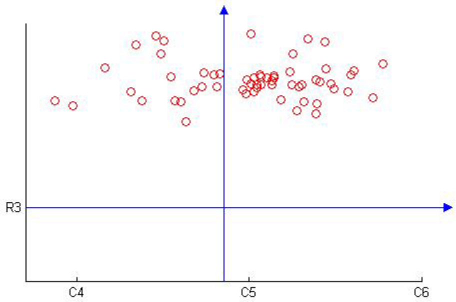


Figure 5-9: Distribution of relevancy degrees of the population for naked body shapes (Fuzzy-ID3)

The sensitivity of the results can be characterized by the distribution of the relevancy degrees of the whole population on the $(Y \times t_i)$ plan. More spread the distribution is, more sensitive the obtained relevancy degrees are to the variation of body shapes. As the population is composed of 60 various representative body shapes, their relevancy degrees should be more spread on the $(Y \times t_i)$ plan. This is the case of Fuzzy-ID3 (Figure 5-9). In the results of CART (Figure 5-8), the distribution of the relevancy degrees is rather compact and then insensitive to the variation of body shapes. In this sense, Fuzzy-ID3 is more efficient than CART.

The same phenomenon can also be observed in Figure 5-10 (for CART) and Figure 5-11 (Fuzzy-ID3), which give the distributions of relevancy degrees of the population for body shapes with different design styles.

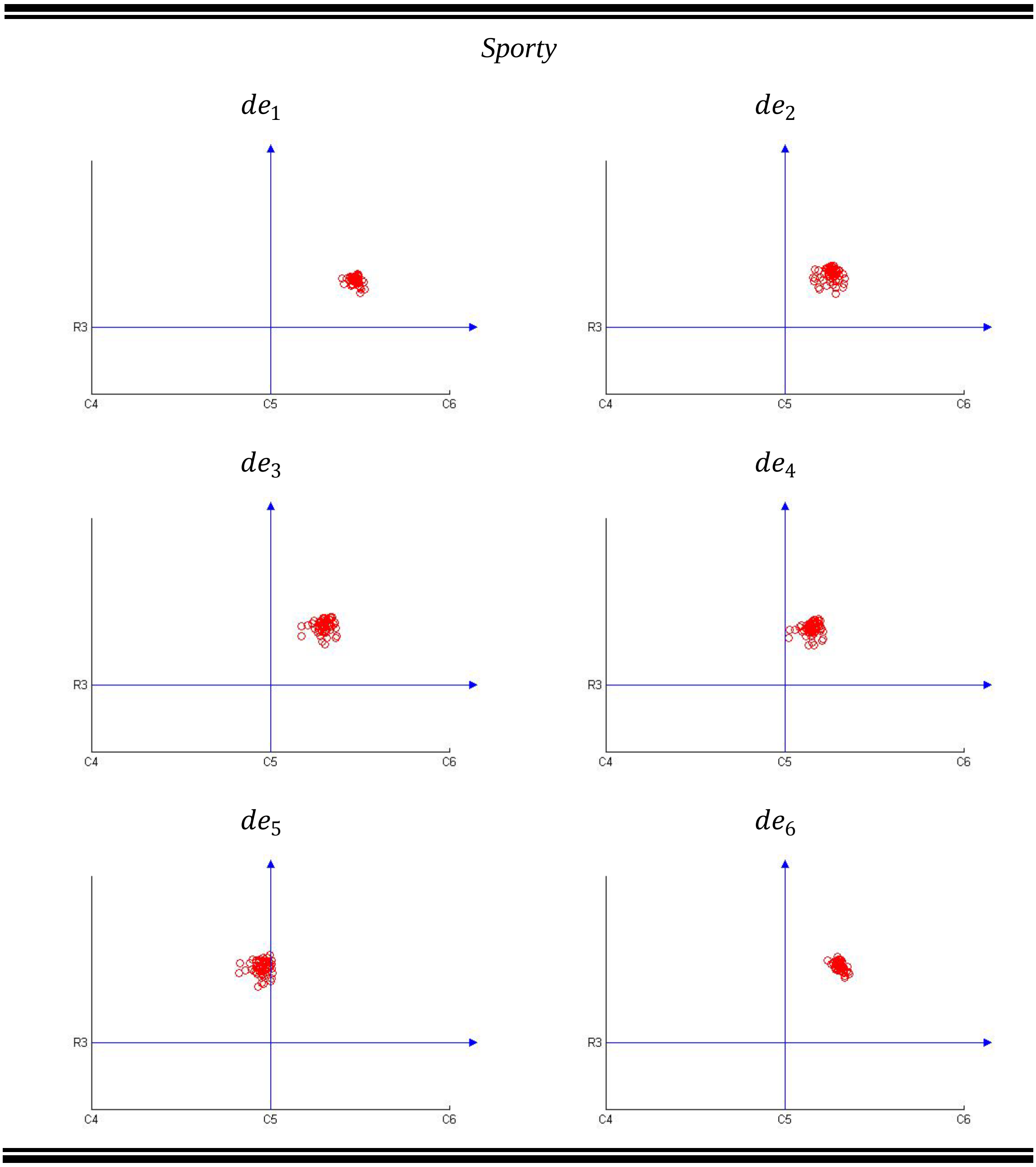


Figure 5-10: Distribution of relevancy degrees of the population for body shapes with different design styles (CART)

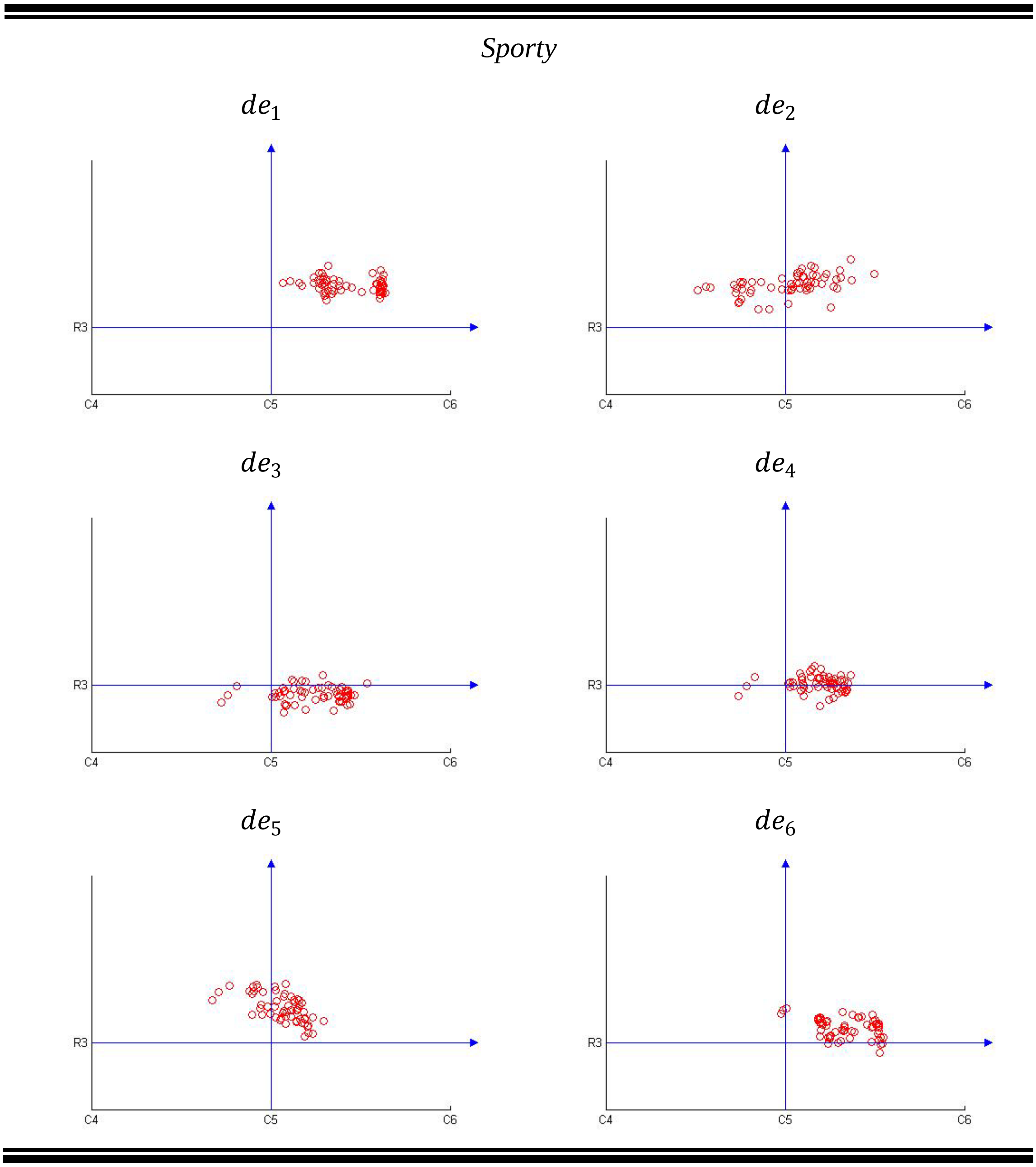


Figure 5-11: Distribution of relevancy degrees of the population for body shapes with different design styles (Fuzzy-ID3)

General Conclusion and Prospect

With increasing needs towards personalized and low-price products in mass markets, mass customization has become an effective solution for many textile/fashion companies. In this context, fashion designers need to integrate their experience and knowledge on target market into their process of design while preserving their original design concepts. Therefore, setting up a suitable compromise between marketing and design concept becomes the key to success for all fashion designers. According to this idea, we propose a fashion design support system for helping designers to evaluate a set of new designs by systematically taking into account human perceptions.

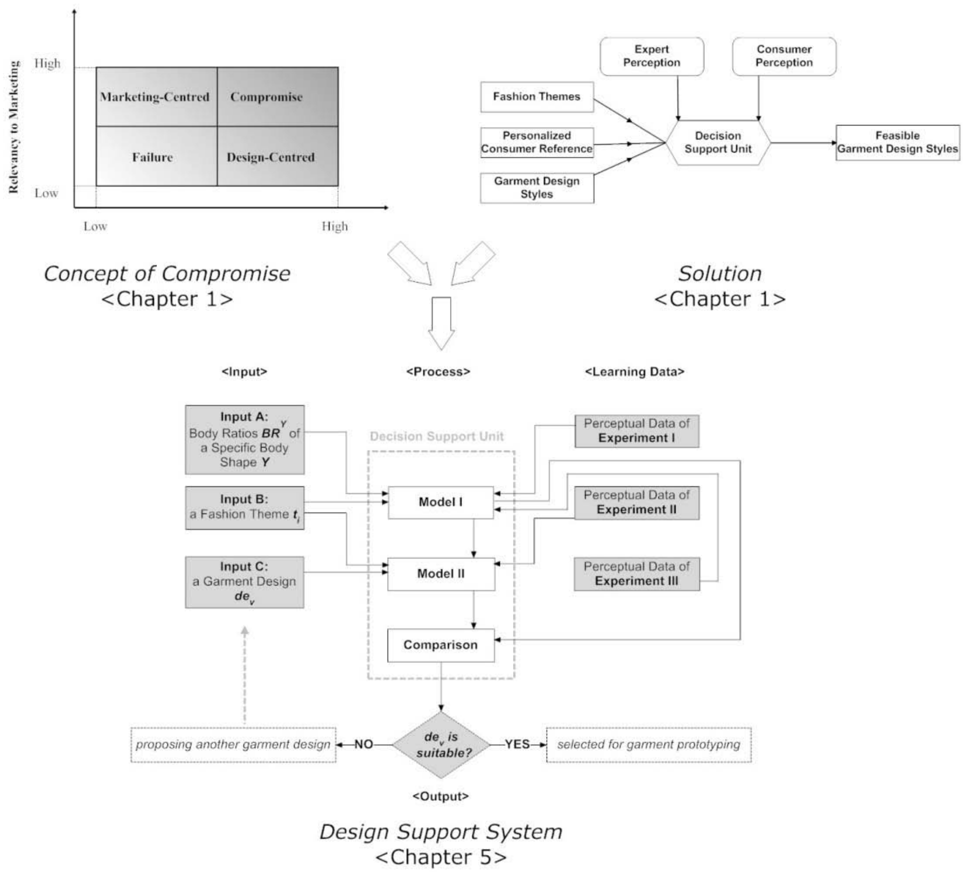


Figure: The general conceptual scheme of my thesis

The general conceptual scheme of my thesis is given in the previous figure. First, we characterize and acquire fashion expert perception and consumer perception on the human body shapes. The human perception on body shapes is composed of two levels: basic perception describing the nature of body shapes independent of their socio-cultural contexts (design expert perception), and abstract fashion themes describing aesthetics of body shapes (consumer perception). At the first level, we propose two experiments in order to acquire expert perceptual data (sensory descriptors) on naked virtual body shapes (**Experiment I**) and those with garment design styles (**Experiment II**). Another experiment is carried out for acquiring consumer perceptual data on relations between fashion themes and sensory descriptors (**Experiment III**). Next, the perceptual data of these two levels are formalized and analyzed using fuzzy set theory. The complex relations between the perceptions of these two levels as well as the physical measurements of body shapes are modeled, leading to compute the relevancy degrees of a naked body (**Model I**) and a body with a garment design style (**Model II**) to a given fashion theme.

Model I deals with three relations, i.e. the relation between sensory descriptors and naked body ratios, the relation between fashion themes and sensory descriptors, and the relation between naked body ratios and a specific fashion theme. The first relation is modeled using decision trees. It is an empirical model built by learning from the perceptual data in **Experiment I**. The second relation is modeled using a fuzzy cognitive map. It is a cognitive model built from consumer perceptions of **Experiment III**. These two relations were then combined for computing the relevancy degree of a specific body shape to a given fashion theme.

Model II first treats the fuzzy relation between a new garment design style and a number of reference styles in order to express this new design using its membership degrees to the existing reference styles. Next, we extract the fuzzy relation between the standard body CA170 with each reference style, and the identified sensory descriptors from the expert perceptual data in **Experiment II**. By combining the two previous fuzzy relations and the relation between fashion themes and sensory descriptors, calculated in **Model I**, we obtain the relevancy of the standard body shape with a new garment design to a given fashion theme.

Next, by using the union operation between this relevancy and the output of **Model I** (relevancy of a specific naked body shape to a given fashion theme), we obtain the relevancy of a specific body shape with a specific garment design to a given fashion theme, which constitutes the output of **Model II**.

The outputs of the above two models are compared in the stage of **Comparison** to determine whether a garment design is feasible for a specific body shape in terms of promotion of its relevancy to the fashion theme. **Model I**, **Model II** and **Comparison** constitute together the decision support unit of the proposed design support system.

The proposed design support system is applied in two real cases of design. The first case is aimed to show the specificity of various consumers' body shapes for a required fashion theme. This design strategy is more adapted to realization of personalized high fashion transactions through Internet. The objective of the second case is to apply the proposed design support system to mass fashion market by selecting a set of feasible design styles meeting the needs of the general public. Different from the first case, this design strategy deals with the requirements of one population by providing them feasible mass products with low cost.

In my PhD research, based on the principle of setting up a compromise between marketing and fashion design, we offer a quantitative evaluation criterion for selecting feasible fashion products in a mass market. Another contribution in my thesis is the development of a new classification of human body shapes using human perceptions. It should be more significant than the existing physical measurement-based body shape classification methods, especially in garment design. The classified results are capable of taking into account both aesthetics and physical measurements of human bodies.

The proposed fashion design support system can be further developed towards the concept of mass customization. Using the previous evaluation criterion, we can classify the whole set of design styles into different classes, each corresponding to a specific class of body shapes.

The human perception-based classification of body shapes can be further improved and extended by integrating other physical features of consumers, like skin color and face, and consumer's socio-cultural features such as age, profession and wearing occasion. The new classification will permit to realize a market segmentation for a specific population. For each segmented market, consumers will have similar requirements on fashion products. In the same time, we will also extend the perception-based classification of fashion styles by integrating other design elements, like colors and material textures. The final objective is to find the most appropriate class of design elements for each segmented market. In this way, the customization of fashion products can be realized with high-profit and low-cost.

Bibliography

[1] Altabe, M. & Thompson, J.K. (1993) *Body Image Changes during Early Adulthood*. International Journal of Eating Disorders, Vol. 13, Issue 3, 1993, p. 323–328.

[2] American Marketing Association, Dictionary online, 2011. Available in: http://www.marketingpower.com

[3] Axelrod, R. (1976) *Structure of Decision: The Cognitive Map of Political Elites*. : Princeton University Press, 1976, 421 p.

[4] Baek, S.Y. et al. (2008) *Kansei Factor Space Classified by Information for Kansei Image Modeling*. Applied Mathematics and Computation. Vol. 205, Issue 2, 2008, p. 874-882.

[5] Bartczuk, L. & Rutkowska, D. (2006) *A New Version of the Fuzzy-ID3 Algorithm*. ICAISC 2006, LNAI 4029, 2006, p. 1060-1070.

[6] Beazley, A. (1997) *Size and Fit: Procedures in Undertaking a Survey of Body Measurements*. Journal of Fashion Marketing and Management, Vol.2, Issue 1, 1997, p.55-85.

[7] Berk, R.A. (2008) *Statistical Learning from a Regression Perspective*. New York: Springer Press, 2008, p.103-161.

[8] Blackman, C. (2009) *One Hundred Years of Men wear*. UK: Laurence King Publishing Ltd., 2009, 320 p.

[9] Brangier, E. & Barcenilla, J. (2003) *Concevoir un Produit Facile à Utiliser*. Paris: Editions d'Organisation, 2003, p. 662

[10] Brannon, E.L. (2005) *Fashion Forecasting*. 2nd edition. New York: Fairchild Publication, 2005, 439 p.

[11] Breiman, L. et al. (1984) *Classification and Regression Trees*. Monterey, CA: Wadsworth & Brooks/Cole Advanced Books & Software, 1984, 358 p.

[12] Bruzzi, S. & Gilbson, P.C. (2000) *Fashion Cultures: Theories, Explorations and Analysis*. New York: Routledge Press, 2000, 399 p.

[13] Burns, L.D. & Bryant, N.O. (1997) *The Business of Fashion: Designing, Manufacturing, and*

Marketing. New York: Fairchild Press, 1997, 439 p.

[14] Carpenter, S. & Huffman, K. (2007) *Visualizing Psychology*. : John Wiley & Son Press, 2007, 544 p.

[15] Chevrie, F. & Guely, F. (1998) *La Logique Floue*. Cahier technique n° 191, 1998. Available in: http://www.schneider-electric.com

[16] Chinese National Standard GB/T 1335.1-2008. Beijing: AQSIQ & SAC, 2008.

[17] Cichocka, A. et al. (2007) *Introduction to Modeling of Virtual Garment Design in 3D*. ISC'2007, Delft University of Technology, Netherlands, June 11-13, 2007.

[18] Devarajan, P. et al. (2002) *U.S. Sizing Standards and the U.S. Female Consumer*. Proc of IFFTI Conf, Fashion and Text: the New Frontiers: Design, Technology and Business, Hong Kong, 7-9 Nov., 2002.

[19] Easey, M. (2009) *Fashion Marketing*. 3rd edition, Oxford: Wiley Blackwell Press, 2009, 278 p.

[20] Fan, J. et al. (2004) *Clothing Appearance and Fit: Science and Technology*. Cambridge: Woodhead Publishing Limited and CRC Press, 2004, 240 p.

[21] Flügel, J.C. (1930) *The Psychology of Clothes*. : The Hogarth Press, 1930.

[22] Giboreau, A. et al. (2007) *Defining Sensory Descriptors: Towards Writing Guidelines based on terminology*. Food Quality and Preference. Vol.18, Issue 2, 2007, p. 265-274.

[23] Glenville, T. (2007) *Top to Toe*. UK: Apple Press, 2007, 176 p.

[24] Goldstein, E.B. (2010) *Sensation and Perception*. 8th edition, Wadsworth, Cengage Learning, 2010, 496 p.

[25] Hagiwara, M. (1992) *Extended Fuzzy Cognitive Maps*, Proc. IEEE International Conference on Fuzzy Systems, San Diego, 8-12 March, 1992, p. 795-801.

[26] Han, J. & Kamber, M. (2006) *Data Mining : Concepts and Techniques*. San Francisco: Morgan Kaufmann, 2006, 800 p.

[27] Horn, M.J. & Gurel, L.M.. (1981) *The Second Skin*. 3rd edition, Boston: Houghton Mifflin Company, 1981, 480 p.

[28] Istook, C.L. (2008) *Three-dimensional Body Scanning to Improve Fit*, Advances in apparel Production, edited by Fairhurst C., Cambridge: Woodhead Publishing. 2008, p. 94-116.

[29] Ives, B. & Piccoli, G. (2003) *Custom Made Apparel and Individualized Service at Lands' End*.

Communications of the Association for Information Systems, Vol. 11, Article 3, 2003, p. 79-93.

[30] Jang, J.-S.R. & Sun, C.-T. (1997) *Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence*. 1st edition, Englewood Cliffs, NJ: Prentice Hall, 1997, 614 p.

[31] Janikow, C.Z. (1996) *Exemplar Learning in Fuzzy Decision Trees*. Proceedings of FUZZ-IEEE, 1996, p. 1500-1505.

[32] Janikow, C.Z. (2007) *userMan34*, Resource of FID 3.4, 2007 Available in: http://www.cs.umsl.edu/~janikow/fid

[33] Jones, S.J. (2005) *Le stylisme : Guide des métiers*.: Pyramyd Press, 2005, 240 p.

[34] Kantardzic, M. (2011) *Data Mining: Concept, Models, Methods, and Algorithms*. London: Wiley-Blackwell, 2011, 552 p.

[35] Keiser, S.J. & Garner, B.M. (2003) *Beyond Design: The Synergy of Apparel Product Debel*. New York: Fairchild Press, 2003, 472 p.

[36] Kemp, S.E. et al. (2009) *Sensory Evaluation : A Practical Handbook*. Oxford: John Wiley & Son Press, 2009, 208 p.

[37] Kemsley, R. (1957) *Women's Measurements and Size*. A Study Sponsored by the Joint Clothing Council Limited, London: HMSO, 1957.

[38] Khan, M.S. & Quaddus, M. (2004) *Group Decision Support Using Fuzzy Cognitive Maps for Causal Reasoning. Group Decision and Negotiation*. Issue 13, 2004, p. 463-480.

[39] Kosko, B. (1986) *Fuzzy Cognitive Maps*, International Journal of Man-Machine Studies, Issue 24, 1986, p. 65-75.

[40] Kotlet, P. & Armstrong, G. (2010) *Principles of Marketing*. 13th Global edition, New Jersey: Prentice Hall Press, 2010, 608 p.

[41] Kunick, P. (1984) *Modern Sizing and Pattern Making for Women's and Children's Garments: A Scientific Study in Pattern Construction and a Standard Textbook for the Clothing Industry*. London: Philip Kunick Publications, 1984, 178 p.

[42] Kurzweil, R. (1992) *The Age of Intelligent Machines*. Cambridge: MIT Press, 1992, 580 p.

[43] Lamb, C.S. et al. (1993) *Body Figure Preferences of Men and Women: A Comparison of Two Generations*. Sex Roles, 1993, Issue 28, p. 345-358.

[44] Lee, K.H. (2005) *First Course on Fuzzy Theory and Applications*. Berlin: Springer Press, 2005, 345 p.

[45] Lim, H. et al. (2009) *Advance Mass Customization in Apparel*. Journal of Textile and Apparel: Technology and Management, Vol. 6, No. 1, 2009, p. 1-16.

[46] Lohman, T.G. et al. (1988) *Anthropometric Standardization Reference Manual*. Illinois: Human Kinetics Books, 1988, 184 p.

[47] Mamdani, E.H. & Assilian, S. (1999) *An Experiment in Linguistic Synthesis with a Fuzzy Logic Controller*. International Journal of Human-Computer Studies, Vol.51, Issue 2, 1999, p. 135-147.

[48] Mathworks Support Resources, 2011.
Available in: http://www.mathworks.fr/support/

[49] Oehlhof, M.E.W. et al. (2009) *Self-objectification and Ideal Body Shape for Men and Women*. Body Image. Vol. 6, Issue 4, 2009, p. 308-310.

[50] Oxford Dictionaries Online. UK: Oxford University Press, 2012.
Available in: http://oxforddictionaries.com/

[51] Papageorigiou, E.I. et al. (2008) *Fuzzy Cognitive Map based Decision Support System for Thyroid Diagnosis Management*. FUZZ-IEEE 2008, Fuzzy Systems, 1-6 Jun., 2008, p. 1204-1211.

[52] Pheasant, S. (1986) *Bodyspace Anthropometry Ergonomics and Design*. London: Taylor & Francis, 1986, 275 p.

[53] Piller, F.T. & Tseng, M.M. (2010) *Handbook of Research in Mass Customization and Personalization*. : World Scientific Press, 2010, p. 591-600.

[54] Pine, B.J.II. (1993) *Mass customization.* Boston: Harvard Business School Press, 1993, 333 p.

[55] Quinlan, J.R. (1986) *Induction of Decision Trees*. Machine Learning, Issue 1, 1986, p. 81-106.

[56] Quinlan, J.R. (1988) *An empirical comparison of genetic and decision-tree classifiers*. In Proc. 1988 Int. Conf. Machine Learning (ML'88), San Mateo, CA, 1988, p. 135-141.

[57] Ross, T.J. (2004) *Fuzzy Logic with Engineering Applications*. 2nd edition UK: John Wiley & Son Int, 2004, 628 p.

[58] Russell, S. & Norvig, P. (2010) *Artificial Intelligence: A Modern Approach*. 3rd edition, New Jersey: Prentice Hall, 2010, 1152 p.

[59] Solso, R.L. et al. (2005) *Cognitive Psychology*, 7th edition: Pearson Education Press, 2005, 624 p.

[60] Songer, R. & Udale, J. (2006) *The Fundamentals of Fashion Design*. London: AVA Publishing SA, 2006, 176 p.

[61] Stone, H. & Sidel, J.L. (2004) *Sensory Evaluation Practices*. 3rd edition, California: Elsevier Academic Press, 2004, 408 p.

[62] Suknovic, M. et al. (2012) *Reusable Components in Decision Tree induction Algorithms*. Computational Statistics, Issue 27, 2012, p. 127-148.

[63] Thompson, J.K. et al. (1999) *Exacting beauty: Theory, assessment, and treatment of body image disturbance*. Washington, DC: American Psychological Association, 1999, 396 p.

[64] Tseng, M. & Jiao, J. (2001) *Mass Customization*. Handbook of Industrial Engineering, edited by Salvendy, G., 3rd edition, New York: Wiley Press. pp 684–709, 2001

[65] Tungate, M. (2005) *Fashion Brands: Branding Style From Armani to Zara*. London: Kogan Page Press, 2005, 272 p.

[66] Urban, G.L. & Hauser, J.R. (1993) *Design and Marketing of New Products*. 2nd edition. : Prentice Hall Press, 1993, 670 p.

[67] Varnado-Sullivan, P.J. et al. (2006) *Differences for Gender, Weight, and Exercise in Body Image Disturbance and Eating Disorder Symptoms*. Eating and Weight Disorders, Issue 11, 2006, p. 118-125.

[68] Vasantha Kandasamy, W.B. & Smarandache, F. (2003) *Fuzzy Cognitive Maps and Neutrosophic Cognitive Maps*. Phoenix: Xiquan, 2003, 211 p.

[69] VIRTUAL FASHION TECHNOLOGY, 2007.
Available in: http://fashiontech.wordpress.com/category/mass-custimization

[70] Wilson, J.O. & Rosen D. (2005) *Selection for Rapid Manufacturing Under Epistemic Uncertainty*. Design for Manufacturing and the Life Cycle Conference, 24-28 Sep., 2005. Long Beach, CA: ASME, Vol.4b, p. 451-460.

[71] Winston, P.H. (1992) *Artificial Intelligence*. 3rd edition : Addison Wesley, 1992, 737 p.

[72] Yuan, Y.F. & Shaw, M.J. (1995) *Introduction of Fuzzy Decision Trees*. Fuzzy Sets and

Systems, Vol. 69, Issue 2, 1995, p. 125-139.

[73] Zadeh, L.A. (1965) *Fuzzy Sets*. Information Control, Vol. 8, 1965, p. 338—353.

[74] Zhu, Y. et al. (2010) *A General Methodology for Analyzing Fashion Oriented Textile Products Using Sensory Evaluation*. Food Quality and Preference, Vol. 21, Issue 8, 2010, p. 1068-1076.

Appendix 1

客户感性评估问卷调查

Sensory Evaluation of Semantic Scales

客户编号 Client No.____________________

时尚主题 Fashion Themes		
Sport (T1)	Nature (T2)	Attractive (T3)

关联度 Degree of Relevancy				
非常不相关	比较不相关	一般	比较相关	非常相关
Very Irrelevant	Fairly Irrelevant	Neutral	Fairly Relevant	Very Relevant

感性描述 Sensory Descriptors

Index	中文		Français		English	
S1	肥胖的	苗条的	Gros	Mince	Fat	Thin

S1	Very Irrelevant	Fairly Irrelevant	Neutral	Fairly Relevant	Very Relevant
T1					
T2					
T3					

S2	臃肿的	纤细的	Gras	Maigre	Bulgy	Slim

S2	Very Irrelevant	Fairly Irrelevant	Neutral	Fairly Relevant	Very Relevant
T1					
T2					
T3					

S3	凸感的	凹感的	Enflé	Déformé	Swollen	Dented

S3	Very Irrelevant	Fairly Irrelevant	Neutral	Fairly Relevant	Very Relevant
T1					
T2					
T3					

S4	挺拔的	萎缩的	Baraqué	Gringalet	Forceful	Atrophic

S4	Very Irrelevant	Fairly Irrelevant	Neutral	Fairly Relevant	Very Relevant
T1					
T2					
T3					

S5	高的	矮的	Grand	Petit	Tall	Short

S5	Very Irrelevant	Fairly Irrelevant	Neutral	Fairly Relevant	Very Relevant
T1					
T2					
T3					

S6	宽的	窄的	Large	Étroit	Wide	Narrow

S6	Very Irrelevant	Fairly Irrelevant	Neutral	Fairly Relevant	Very Relevant
T1					
T2					
T3					

S7	厚实的	扁平的	Épais	Élancé	Thick	Flat

S7	Very Irrelevant	Fairly Irrelevant	Neutral	Fairly Relevant	Very Relevant
T1					
T2					
T3					

S8	流线型	非流线型	Longiline	Non-Longiline	Streamline	Non-streamline

S8	Very Irrelevant	Fairly Irrelevant	Neutral	Fairly Relevant	Very Relevant
T1					
T2					

T3					

S9	平滑的	疙瘩的	Belle Ligne	Noueux	Smooth	Knotty

S9	Very Irrelevant	Fairly Irrelevant	Neutral	Fairly Relevant	Very Relevant
T1					
T2					
T3					

S10	丰满的	干瘪的	Bien en chair	Maladif	Fleshly	Shrivel

S10	Very Irrelevant	Fairly Irrelevant	Neutral	Fairly Relevant	Very Relevant
T1					
T2					
T3					

S11	健壮的	柔弱的	Vigoureux	Asthénique	Lusty	Effeminate

S11	Very Irrelevant	Fairly Irrelevant	Neutral	Fairly Relevant	Very Relevant
T1					
T2					
T3					

S12	结实的	脆弱的	Fort	Fragilité	Strong	Fragility

S12	Very Irrelevant	Fairly Irrelevant	Neutral	Fairly Relevant	Very Relevant
T1					
T2					
T3					

S13	弹性的	非弹性的	Élastique	Non-élastique	Elastic	Inelastic

S13	Very Irrelevant	Fairly Irrelevant	Neutral	Fairly Relevant	Very Relevant
T1					

T2					
T3					

S14	笨拙的	灵巧的	Maladroit	Dynamique	Awkward	deft

S14	Very Irrelevant	Fairly Irrelevant	Neutral	Fairly Relevant	Very Relevant
T1					
T2					
T3					

S15	硕大的	微小的	Immense	Nain	Huge	Cabinet

S15	Very Irrelevant	Fairly Irrelevant	Neutral	Fairly Relevant	Very Relevant
T1					
T2					
T3					

S16	谐调的	失衡的	Harmonieux	Déséquilibré	Harmonious	Unbalanced

S16	Very Irrelevant	Fairly Irrelevant	Neutral	Fairly Relevant	Very Relevant
T1					
T2					
T3					

S17	正常的	奇特的	Standand	Exceptionnel	Normal	Unique

S17	Very Irrelevant	Fairly Irrelevant	Neutral	Fairly Relevant	Very Relevant
T1					
T2					
T3					

S18	有型的	无形的	Élégant	Peu élégant	Stylish	Unstylish

S18	Very Irrelevant	Fairly Irrelevant	Neutral	Fairly Relevant	Very Relevant

T1					
T2					
T3					

S19	肌肉的	脂肪的	Musclé	Corpulent	Muscular	Sebaceous

S19	Very Irrelevant	Fairly Irrelevant	Neutral	Fairly Relevant	Very Relevant
T1					
T2					
T3					

S20	动感的	懒惰的	Vif	Lent	Vivid	Lazy

S20	Very Irrelevant	Fairly Irrelevant	Neutral	Fairly Relevant	Very Relevant
T1					
T2					
T3					

S21	重的	轻的	Lourd	Léger;	Heavy	Light

S21	Very Irrelevant	Fairly Irrelevant	Neutral	Fairly Relevant	Very Relevant
T1					
T2					
T3					

S22	性感的	不性感的	Sexy	pas sexy	Sexy	Unsexy

S22	Very Irrelevant	Fairly Irrelevant	Neutral	Fairly Relevant	Very Relevant
T1					
T2					
T3					

Appendix 2-a: Output of Model I in Case I (CART)

Attractive; Naked; CART									
	REL								
Consumer01	0.0000	0.1200	0.1600	0.1600	0.2400	0.2000	0.2400	0.2400	0.0800
	0.0000	0.3200	0.2175	0.3200	0.2800	0.2800	0.2000	0.2800	0.1200
	0.0000	0.4000	0.2400	0.2800	0.2628	0.5012	0.4988	0.2400	0.2000
	0.0000	0.4000	0.4400	0.3634	0.4000	0.4400	0.3600	0.2814	0.2800
	0.0000	0.3715	0.3801	0.6000	0.4400	0.4237	0.5200	0.2400	0.4400
Consumer02	0.0000	0.1200	0.1600	0.1600	0.2400	0.2400	0.2400	0.2400	0.0800
	0.0000	0.2800	0.2800	0.3178	0.2800	0.3200	0.2000	0.2800	0.1200
	0.0000	0.4000	0.2400	0.2800	0.4000	0.4663	0.5200	0.2400	0.1502
	0.0000	0.4000	0.4400	0.3600	0.4000	0.4400	0.3600	0.3104	0.1502
	0.0000	0.3200	0.4194	0.6000	0.4400	0.4216	0.5200	0.2400	0.1502
Consumer03	0.0000	0.1200	0.1600	0.1600	0.2400	0.2400	0.2400	0.2400	0.0000
	0.0000	0.2985	0.2800	0.3200	0.2800	0.3200	0.2000	0.2800	0.1200
	0.0000	0.4000	0.2400	0.2800	0.4000	0.4810	0.5190	0.2400	0.2000
	0.0000	0.4000	0.4400	0.3600	0.4000	0.4400	0.3200	0.2933	0.2400
	0.0000	0.3604	0.3842	0.6000	0.4400	0.4365	0.5200	0.2400	0.3592

Appendix 2-b: Output of Model I in Case I (Fuzzy-ID3)

Attractive; Naked; Fuzzy-ID3									
	REL								
Consumer01	0.0800	0.1743	0.2400	0.2400	0.2400	0.2400	0.1600	0.1600	0.0800
	0.0860	0.2473	0.2923	0.3200	0.2567	0.2800	0.2800	0.2800	0.1657
	0.0860	0.2400	0.2930	0.3117	0.4000	0.4533	0.2523	0.4227	0.2000
	0.0860	0.2800	0.3313	0.3600	0.3600	0.3380	0.4400	0.3257	0.2400
	0.0860	0.3200	0.2800	0.3003	0.5200	0.5377	0.4887	0.3330	0.3337
Consumer02	0.2000	0.2400	0.2400	0.2400	0.2400	0.0800	0.0800	0.0800	0.0000
	0.3200	0.2800	0.3200	0.3200	0.2800	0.2800	0.2800	0.1867	0.0000
	0.3333	0.2800	0.4000	0.3493	0.4800	0.2400	0.2400	0.1867	0.0000
	0.2000	0.3200	0.3600	0.4400	0.4400	0.4000	0.4400	0.1867	0.0000
	0.2000	0.3187	0.4400	0.5200	0.3293	0.7540	0.4000	0.1867	0.0000
Consumer03	0.0000	0.2400	0.1487	0.2020	0.2400	0.2400	0.1600	0.0800	0.0800
	0.0000	0.1200	0.2000	0.2350	0.3200	0.2800	0.2800	0.2800	0.2170
	0.0000	0.2000	0.3060	0.4000	0.5200	0.2400	0.2847	0.2000	0.2000
	0.0000	0.3333	0.2630	0.3333	0.4400	0.3813	0.4400	0.2717	0.2170
	0.0000	0.2193	0.2630	0.3200	0.5200	0.3813	0.5517	0.2717	0.2153

Appendix 3-a: Output of Model II in Case I (CART)

Attractive; de_1; CART									
	REL								
Consumer01	0.0000	0.2400	0.1600	0.2400	0.2400	0.2000	0.2400	0.2400	0.2400
	0.0000	0.3200	0.2175	0.3200	0.2800	0.2800	0.3200	0.3200	0.1200
	0.0000	0.4000	0.3333	0.3333	0.5200	0.5012	0.4988	0.2800	0.2400
	0.0000	0.4000	0.4400	0.3634	0.4000	0.4400	0.3600	0.4400	0.4400
	0.0000	0.3715	0.4400	0.6000	0.4400	0.4237	0.8000	0.4400	0.4400
Consumer02	0.0000	0.2400	0.1600	0.2400	0.2400	0.2400	0.2400	0.2400	0.2400
	0.0000	0.2800	0.2800	0.3200	0.2800	0.3200	0.3200	0.3200	0.1200
	0.0000	0.4000	0.3333	0.3333	0.5200	0.4663	0.5200	0.2800	0.2400
	0.0000	0.4000	0.4400	0.3600	0.4000	0.4400	0.3600	0.4400	0.4400
	0.0000	0.3333	0.4400	0.6000	0.4400	0.4216	0.8000	0.4400	0.3333
Consumer03	0.0000	0.2400	0.1600	0.2400	0.2400	0.2400	0.2400	0.2400	0.2400
	0.0000	0.2985	0.2800	0.3200	0.2800	0.3200	0.3200	0.3200	0.1200
	0.0000	0.4000	0.3333	0.3333	0.5200	0.4810	0.5190	0.2800	0.2400
	0.0000	0.4000	0.4400	0.3600	0.4000	0.4400	0.3333	0.4400	0.4400
	0.0000	0.3604	0.4400	0.6000	0.4400	0.4365	0.8000	0.4400	0.3592

Attractive; de_2; CART									
	REL								
Consumer01	0.0000	0.2400	0.1600	0.1600	0.2400	0.2400	0.2400	0.2400	0.0800
	0.0000	0.3200	0.3200	0.3200	0.2800	0.3200	0.3200	0.2800	0.1200
	0.0000	0.4000	0.2800	0.2800	0.3333	0.5012	0.4988	0.5200	0.2000
	0.0000	0.4000	0.4400	0.3634	0.4400	0.4400	0.3600	0.3600	0.2800
	0.0000	0.3715	0.3801	0.6000	0.4400	0.4237	0.5200	0.3333	0.4400
Consumer02	0.0000	0.2400	0.1600	0.1600	0.2400	0.2400	0.2400	0.2400	0.0800
	0.0000	0.2800	0.3200	0.3178	0.2800	0.3200	0.3200	0.2800	0.1200
	0.0000	0.4000	0.2800	0.2800	0.4000	0.4663	0.5200	0.5200	0.1502
	0.0000	0.4000	0.4400	0.3600	0.4400	0.4400	0.3600	0.3600	0.1502
	0.0000	0.3333	0.4194	0.6000	0.4400	0.4216	0.5200	0.3333	0.1502
Consumer03	0.0000	0.2400	0.1600	0.1600	0.2400	0.2400	0.2400	0.2400	0.0000
	0.0000	0.2985	0.3200	0.3200	0.2800	0.3200	0.3200	0.2800	0.1200
	0.0000	0.4000	0.2800	0.2800	0.4000	0.4810	0.5190	0.5200	0.2000
	0.0000	0.4000	0.4400	0.3600	0.4400	0.4400	0.3333	0.3600	0.2400
	0.0000	0.3604	0.3842	0.6000	0.4400	0.4365	0.5200	0.3333	0.3592

Attractive; de_3; CART									
	REL								
Consumer01	0.0200	0.1800	0.1600	0.1800	0.2400	0.2000	0.2400	0.2400	0.1800
	0.0300	0.3200	0.2175	0.3200	0.2800	0.2800	0.2400	0.2800	0.1200
	0.0500	0.4000	0.2500	0.2800	0.3900	0.5012	0.4988	0.2400	0.2000
	0.0700	0.4000	0.4400	0.3634	0.4000	0.4400	0.3600	0.3300	0.3300
	0.0800	0.3715	0.3801	0.6000	0.4400	0.4237	0.6000	0.3300	0.4400
Consumer02	0.0200	0.1800	0.1600	0.1800	0.2400	0.2400	0.2400	0.2400	0.1800
	0.0300	0.2800	0.2800	0.3178	0.2800	0.3200	0.2400	0.2800	0.1200
	0.0500	0.4000	0.2500	0.2800	0.4000	0.4663	0.5200	0.2400	0.1800
	0.0700	0.4000	0.4400	0.3600	0.4000	0.4400	0.3600	0.3300	0.3300
	0.0800	0.3200	0.4194	0.6000	0.4400	0.4216	0.6000	0.3300	0.2500
Consumer03	0.0200	0.1800	0.1600	0.1800	0.2400	0.2400	0.2400	0.2400	0.1800
	0.0300	0.2985	0.2800	0.3200	0.2800	0.3200	0.2400	0.2800	0.1200
	0.0500	0.4000	0.2500	0.2800	0.4000	0.4810	0.5190	0.2400	0.2000
	0.0700	0.4000	0.4400	0.3600	0.4000	0.4400	0.3200	0.3300	0.3300
	0.0800	0.3604	0.3842	0.6000	0.4400	0.4365	0.6000	0.3300	0.3592

Appendix 3-b: Output of Model II in Case I (Fuzzy-ID3)

Attractive; de_1; Fuzzy-ID3

	REL								
Consumer01	0.0800	0.2400	0.2400	0.2400	0.2400	0.2400	0.2400	0.1600	0.2400
	0.0860	0.2800	0.2923	0.3200	0.2800	0.2800	0.3200	0.3200	0.1657
	0.0860	0.2400	0.3333	0.3333	0.5200	0.4533	0.4800	0.4227	0.2400
	0.0860	0.3333	0.3313	0.3600	0.3600	0.3380	0.4400	0.4400	0.4400
	0.0860	0.3333	0.4400	0.3333	0.5200	0.5377	0.8000	0.4400	0.3337
Consumer02	0.2000	0.2400	0.2400	0.2400	0.2400	0.1600	0.2400	0.1200	0.2400
	0.3200	0.2800	0.3200	0.3200	0.2800	0.2800	0.3200	0.3200	0.1200
	0.3333	0.2800	0.4000	0.3493	0.5200	0.3333	0.4800	0.2800	0.2400
	0.2000	0.3333	0.3600	0.4400	0.4400	0.4000	0.4400	0.4400	0.4400
	0.2000	0.3333	0.4400	0.5200	0.3293	0.7540	0.8000	0.4400	0.3333
Consumer03	0.0000	0.2400	0.1600	0.2400	0.2400	0.2400	0.2400	0.1200	0.2400
	0.0000	0.2800	0.2000	0.3200	0.3200	0.2800	0.3200	0.3200	0.2170
	0.0000	0.2000	0.3333	0.4000	0.5200	0.3333	0.4800	0.2800	0.2400
	0.0000	0.3333	0.2800	0.3333	0.4400	0.3813	0.4400	0.4400	0.4400
	0.0000	0.3333	0.4400	0.3333	0.5200	0.3813	0.8000	0.4400	0.3333

Attractive; de_2; Fuzzy-ID3

	REL								
Consumer01	0.0800	0.2400	0.2400	0.2400	0.2400	0.2400	0.2400	0.2400	0.0800
	0.0860	0.2800	0.3200	0.3200	0.2567	0.3200	0.3200	0.2800	0.1657
	0.0860	0.2400	0.2930	0.3117	0.4000	0.4533	0.4000	0.5200	0.2000
	0.0860	0.3200	0.3333	0.3600	0.4400	0.3380	0.4400	0.3600	0.2400
	0.0860	0.3333	0.3333	0.3333	0.5200	0.5377	0.4887	0.3333	0.3337
Consumer02	0.2000	0.2400	0.2400	0.2400	0.2400	0.2400	0.2400	0.2400	0.0000
	0.3200	0.2800	0.3200	0.3200	0.2800	0.3200	0.3200	0.2800	0.0000
	0.3333	0.2800	0.4000	0.3493	0.4800	0.3333	0.4000	0.5200	0.0000
	0.2000	0.3200	0.3600	0.4400	0.4400	0.4000	0.4400	0.3600	0.0000
	0.2000	0.3333	0.4400	0.5200	0.3333	0.7540	0.4400	0.3333	0.0000
Consumer03	0.0000	0.2400	0.1600	0.2020	0.2400	0.2400	0.2400	0.2400	0.0800
	0.0000	0.2800	0.3200	0.2350	0.3200	0.3200	0.3200	0.2800	0.2170
	0.0000	0.2000	0.3060	0.4000	0.5200	0.3333	0.4000	0.5200	0.2000
	0.0000	0.3333	0.3333	0.3333	0.4400	0.3813	0.4400	0.3600	0.2170
	0.0000	0.3333	0.3333	0.3333	0.5200	0.3813	0.5517	0.3333	0.2153

Attractive; de_3; Fuzzy-ID3									
	REL								
Consumer01	0.0800	0.1800	0.2400	0.2400	0.2400	0.2400	0.1800	0.1600	0.1800
	0.0860	0.2473	0.2923	0.3200	0.2567	0.2800	0.2800	0.2800	0.1657
	0.0860	0.2400	0.2930	0.3117	0.4000	0.4533	0.3600	0.4227	0.2000
	0.0860	0.2800	0.3313	0.3600	0.3600	0.3380	0.4400	0.3300	0.3300
	0.0860	0.3200	0.3300	0.3003	0.5200	0.5377	0.6000	0.3330	0.3337
Consumer02	0.2000	0.2400	0.2400	0.2400	0.2400	0.1200	0.1800	0.0900	0.1800
	0.3200	0.2800	0.3200	0.3200	0.2800	0.2800	0.2800	0.2400	0.0900
	0.3333	0.2800	0.4000	0.3493	0.4800	0.2500	0.3600	0.2100	0.1800
	0.2000	0.3200	0.3600	0.4400	0.4400	0.4000	0.4400	0.3300	0.3300
	0.2000	0.3187	0.4400	0.5200	0.3293	0.7540	0.6000	0.3300	0.2500
Consumer03	0.0200	0.2400	0.1487	0.2020	0.2400	0.2400	0.1800	0.0900	0.1800
	0.0300	0.2100	0.2000	0.2400	0.3200	0.2800	0.2800	0.2800	0.2170
	0.0500	0.2000	0.3060	0.4000	0.5200	0.2500	0.3600	0.2100	0.2000
	0.0700	0.3333	0.2630	0.3333	0.4400	0.3813	0.4400	0.3300	0.3300
	0.0800	0.2500	0.3300	0.3200	0.5200	0.3813	0.6000	0.3300	0.2500

Appendix 4: Measurement Database in Case II

	bm_1	bm_2	bm_3	bm_4	bm_5	bm_5
Consumer01	169	53.5	89.5	37	76.5	94
Consumer02	177	59	80.5	36	66.5	91
Consumer03	175	58	84.5	38	71.5	92
Consumer04	183.3	60.1	91	38.5	74	96
Consumer05	168.5	53	81	37.5	67	88
Consumer06	168.5	55	78.5	36.5	63	89
Consumer07	164	51.5	86	37	67	91.5
Consumer08	172	55.5	97.5	41	87.5	101.5
Consumer09	164.5	52	82.5	40	66.5	86
Consumer10	169.5	56.5	81	38	67.5	90
Consumer11	171.5	54.5	80	36	65	87
Consumer12	185.5	59.8	86.5	39	68	92.5
Consumer13	170	59	94	39.5	76.5	89.5
Consumer14	176.5	58	97.5	41.5	83.5	103.5
Consumer15	171	54	96	40	73.5	94.5
Consumer16	173.5	56	88	37	69.5	89
Consumer17	168.2	52	84.5	38	65	89
Consumer18	171	57	90	40.5	71	96
Consumer19	183.3	62.8	99.5	39	84.5	102
Consumer20	173	53.5	86.8	39	80	96.5
Consumer21	178.5	58.5	99	38.4	88	99.5
Consumer22	173.5	54	99	44	90	109
Consumer23	171	55	82	38.5	67	88
Consumer24	175	56	86	40.5	78	92
Consumer25	176	57	81	35.9	72	94
Consumer26	171.8	54	82	38.5	64.5	84.5
Consumer27	184	62	94	41	75.5	94.5
Consumer28	160	50.5	83.5	40	65	87.5
Consumer29	163.5	51	85.5	39	63.5	87.5
Consumer30	174	58	86	38.6	70	91.5
Consumer31	168	55	83	40.5	68	90
Consumer32	175.4	57.5	90.5	39.5	78.5	94
Consumer33	162.5	49	84.6	36.5	68.8	86.1
Consumer34	172.2	60	92	37	74	90
Consumer35	162.5	51.2	88.5	38.6	77.4	94.4
Consumer36	165	53.6	86	36.8	74	91
Consumer37	187	61.5	94	39.2	83.9	96
Consumer38	164.2	54.5	82.5	37.7	71.1	84.9
Consumer39	161.5	53.2	83.1	34.9	67.5	87.5

Consumer40	169.2	53.8	83.5	37.3	67.3	93.5
Consumer41	172	57	90.8	37.2	72	93.6
Consumer42	180	59.7	97	40.7	81	100.5
Consumer43	173.8	57.2	83.3	38.5	75	110
Consumer44	175	55.5	84	38	69.5	94.5
Consumer45	175.8	60.5	94	44	79	101.5
Consumer46	169.2	52.5	83	38.1	68.5	91.5
Consumer47	174.8	53	88	37.5	71	99
Consumer48	165.8	52.5	82	36	67	88
Consumer49	163	55.5	80	37	65	84.5
Consumer50	172.2	58	99	44	83	97
Consumer51	175.6	59	94	41.8	79.5	99
Consumer52	174	56	91.3	39.8	81.9	95.6
Consumer53	168.1	55	90.5	40.5	76	90
Consumer54	176.8	56.6	89.6	38.2	78.4	94.2
Consumer55	166.8	52.7	85.9	39.5	70.8	90
Consumer56	173.4	58.6	97.1	39.1	79.5	100.1
Consumer57	173	56	93.5	41.2	77	92
Consumer58	164	54.6	94	39	75	95.4
Consumer59	177	59	97	38.5	78	93.5
Consumer60	167	53.9	87	35.4	68	91.8
					Unit:	cm

Appendix 5-a: Decision Output in Case II (CART)

Sporty	de_1	de_2	de_3	de_4	de_5	de_6
Consumer01	NO	NO	NO	NO	NO	NO
Consumer02	YES	NO	YES	NO	NO	YES
Consumer03	YES	NO	NO	NO	NO	YES
Consumer04	YES	NO	NO	NO	NO	YES
Consumer05	YES	NO	NO	NO	NO	YES
Consumer06	YES	NO	YES	NO	NO	YES
Consumer07	YES	NO	NO	NO	NO	YES
Consumer08	YES	YES	YES	NO	NO	YES
Consumer09	YES	YES	YES	YES	YES	YES
Consumer10	YES	NO	NO	NO	NO	YES
Consumer11	YES	NO	YES	NO	NO	YES
Consumer12	YES	NO	NO	NO	NO	YES
Consumer13	YES	NO	NO	NO	NO	YES
Consumer14	YES	NO	YES	NO	NO	YES
Consumer15	YES	NO	YES	NO	NO	YES
Consumer16	YES	NO	NO	NO	NO	YES
Consumer17	YES	NO	NO	NO	NO	YES
Consumer18	YES	NO	YES	NO	NO	YES
Consumer19	NO	NO	NO	NO	NO	NO
Consumer20	YES	NO	NO	NO	NO	YES
Consumer21	YES	NO	NO	NO	NO	YES
Consumer22	YES	YES	YES	YES	NO	YES
Consumer23	YES	NO	NO	NO	NO	YES
Consumer24	YES	NO	NO	NO	NO	YES
Consumer25	YES	NO	NO	NO	NO	YES
Consumer26	YES	NO	NO	NO	NO	YES
Consumer27	YES	NO	NO	NO	NO	NO
Consumer28	YES	YES	YES	YES	NO	YES
Consumer29	YES	NO	YES	NO	NO	YES
Consumer30	YES	NO	NO	NO	NO	YES
Consumer31	YES	YES	YES	NO	NO	YES
Consumer32	YES	NO	NO	NO	NO	YES
Consumer33	YES	NO	NO	NO	NO	NO
Consumer34	NO	NO	NO	NO	NO	NO
Consumer35	YES	YES	YES	NO	NO	YES
Consumer36	YES	NO	NO	NO	NO	YES
Consumer37	YES	NO	NO	NO	NO	YES
Consumer38	YES	NO	NO	NO	NO	YES
Consumer39	NO	NO	NO	NO	NO	NO

Consumer40	NO	NO	NO	NO	NO	NO
Consumer41	NO	NO	NO	NO	NO	NO
Consumer42	YES	NO	NO	NO	NO	NO
Consumer43	YES	NO	NO	NO	NO	YES
Consumer44	YES	NO	NO	NO	NO	YES
Consumer45	YES	YES	YES	YES	NO	YES
Consumer46	YES	NO	NO	NO	NO	YES
Consumer47	NO	NO	NO	NO	NO	NO
Consumer48	YES	NO	NO	NO	NO	NO
Consumer49	YES	NO	NO	NO	NO	YES
Consumer50	YES	YES	YES	YES	NO	YES
Consumer51	YES	YES	YES	NO	NO	YES
Consumer52	YES	NO	NO	NO	NO	YES
Consumer53	YES	YES	YES	NO	NO	YES
Consumer54	YES	NO	NO	NO	NO	YES
Consumer55	YES	NO	YES	NO	NO	YES
Consumer56	YES	NO	NO	NO	NO	NO
Consumer57	YES	NO	YES	NO	NO	YES
Consumer58	YES	NO	YES	NO	NO	YES
Consumer59	NO	NO	NO	NO	NO	NO
Consumer60	NO	NO	NO	NO	NO	NO

Nature	de_1	de_2	de_3	de_4	de_5	de_6
Consumer01	NO	YES	NO	NO	NO	YES
Consumer02	YES	YES	YES	NO	NO	YES
Consumer03	YES	YES	NO	NO	NO	YES
Consumer04	YES	YES	NO	NO	NO	YES
Consumer05	YES	YES	NO	NO	NO	YES
Consumer06	YES	YES	YES	NO	NO	YES
Consumer07	YES	YES	NO	NO	NO	YES
Consumer08	YES	YES	NO	NO	NO	YES
Consumer09	YES	YES	YES	YES	YES	YES
Consumer10	YES	YES	NO	NO	NO	YES
Consumer11	YES	YES	YES	NO	NO	YES
Consumer12	YES	YES	YES	NO	NO	YES
Consumer13	NO	YES	NO	NO	NO	YES
Consumer14	YES	YES	NO	NO	NO	YES
Consumer15	NO	YES	NO	NO	NO	YES
Consumer16	YES	YES	NO	NO	NO	YES
Consumer17	YES	YES	NO	NO	NO	YES
Consumer18	YES	YES	NO	NO	NO	YES
Consumer19	NO	YES	NO	NO	NO	YES

Consumer20	YES	YES	NO	NO	NO	YES
Consumer21	NO	YES	NO	NO	NO	YES
Consumer22	YES	YES	YES	NO	YES	YES
Consumer23	YES	YES	NO	NO	NO	YES
Consumer24	YES	YES	NO	NO	NO	YES
Consumer25	YES	YES	NO	NO	NO	YES
Consumer26	NO	YES	NO	NO	NO	YES
Consumer27	NO	YES	NO	NO	NO	YES
Consumer28	YES	YES	YES	NO	YES	YES
Consumer29	YES	YES	NO	NO	NO	YES
Consumer30	YES	YES	NO	NO	NO	YES
Consumer31	YES	YES	YES	NO	NO	YES
Consumer32	YES	YES	NO	NO	NO	YES
Consumer33	YES	YES	NO	NO	NO	YES
Consumer34	YES	YES	NO	NO	NO	YES
Consumer35	YES	YES	NO	NO	NO	YES
Consumer36	YES	YES	NO	NO	NO	YES
Consumer37	YES	YES	NO	NO	NO	YES
Consumer38	NO	YES	NO	NO	NO	YES
Consumer39	NO	YES	NO	NO	NO	YES
Consumer40	YES	YES	NO	NO	NO	YES
Consumer41	NO	YES	NO	NO	NO	YES
Consumer42	NO	YES	NO	NO	NO	YES
Consumer43	NO	YES	NO	NO	NO	YES
Consumer44	YES	YES	NO	NO	NO	YES
Consumer45	YES	YES	YES	YES	YES	YES
Consumer46	YES	YES	NO	NO	NO	YES
Consumer47	NO	YES	NO	NO	NO	YES
Consumer48	YES	YES	NO	NO	NO	YES
Consumer49	NO	YES	NO	NO	NO	YES
Consumer50	YES	YES	YES	NO	YES	YES
Consumer51	YES	YES	NO	NO	NO	YES
Consumer52	YES	YES	NO	NO	NO	YES
Consumer53	YES	YES	YES	NO	NO	YES
Consumer54	YES	YES	NO	NO	NO	YES
Consumer55	YES	YES	NO	NO	NO	YES
Consumer56	NO	YES	NO	NO	NO	YES
Consumer57	YES	YES	NO	NO	NO	YES
Consumer58	YES	YES	NO	NO	NO	YES
Consumer59	NO	YES	NO	NO	NO	YES
Consumer60	NO	YES	NO	NO	NO	YES

Attractive	de_1	de_2	de_3	de_4	de_5	de_6
Consumer01	YES	YES	NO	NO	NO	NO
Consumer02	YES	YES	YES	YES	NO	YES
Consumer03	YES	YES	YES	NO	NO	NO
Consumer04	YES	YES	NO	NO	NO	NO
Consumer05	YES	YES	YES	NO	NO	NO
Consumer06	YES	YES	YES	YES	NO	NO
Consumer07	YES	YES	NO	NO	NO	NO
Consumer08	YES	YES	YES	NO	NO	NO
Consumer09	YES	YES	YES	YES	NO	YES
Consumer10	YES	YES	YES	NO	NO	NO
Consumer11	YES	YES	YES	YES	NO	YES
Consumer12	YES	YES	YES	NO	NO	NO
Consumer13	YES	YES	NO	NO	NO	NO
Consumer14	YES	YES	YES	NO	NO	NO
Consumer15	YES	YES	NO	NO	NO	NO
Consumer16	YES	YES	NO	NO	NO	NO
Consumer17	YES	YES	NO	NO	NO	NO
Consumer18	YES	YES	YES	NO	NO	NO
Consumer19	YES	YES	NO	NO	NO	NO
Consumer20	YES	YES	YES	NO	NO	NO
Consumer21	YES	YES	YES	YES	NO	YES
Consumer22	YES	YES	YES	NO	NO	YES
Consumer23	YES	YES	NO	NO	NO	NO
Consumer24	YES	YES	YES	NO	NO	NO
Consumer25	YES	YES	YES	NO	NO	NO
Consumer26	YES	YES	NO	NO	NO	NO
Consumer27	YES	YES	NO	NO	NO	NO
Consumer28	YES	YES	YES	NO	NO	YES
Consumer29	YES	YES	NO	NO	NO	NO
Consumer30	YES	YES	NO	NO	NO	NO
Consumer31	YES	YES	YES	NO	NO	NO
Consumer32	YES	YES	NO	NO	NO	NO
Consumer33	YES	YES	NO	NO	NO	NO
Consumer34	YES	YES	NO	NO	NO	NO
Consumer35	YES	YES	YES	NO	NO	NO
Consumer36	YES	YES	NO	NO	NO	NO
Consumer37	YES	YES	NO	NO	NO	NO
Consumer38	YES	YES	NO	NO	NO	NO
Consumer39	YES	YES	NO	NO	NO	NO
Consumer40	YES	YES	NO	NO	NO	NO
Consumer41	YES	YES	NO	NO	NO	NO
Consumer42	YES	YES	NO	NO	NO	NO

Consumer43	YES	NO	NO	NO	NO	NO
Consumer44	YES	YES	YES	NO	NO	NO
Consumer45	YES	YES	YES	NO	NO	YES
Consumer46	YES	YES	YES	NO	NO	NO
Consumer47	YES	YES	NO	NO	NO	NO
Consumer48	YES	YES	NO	NO	NO	NO
Consumer49	YES	YES	NO	NO	NO	NO
Consumer50	YES	YES	YES	NO	NO	YES
Consumer51	YES	YES	YES	NO	NO	NO
Consumer52	YES	YES	YES	NO	NO	NO
Consumer53	YES	YES	YES	NO	NO	NO
Consumer54	YES	YES	NO	NO	NO	NO
Consumer55	YES	YES	NO	NO	NO	NO
Consumer56	YES	YES	NO	NO	NO	NO
Consumer57	YES	NO	YES	NO	NO	NO
Consumer58	YES	NO	YES	NO	NO	NO
Consumer59	YES	YES	NO	NO	NO	NO
Consumer60	YES	YES	NO	NO	NO	NO

Appendix 5-b: Decision Output in Case II (Fuzzy-ID3)

Sporty	de_1	de_2	de_3	de_4	de_5	de_6
Consumer01	NO	NO	NO	NO	NO	NO
Consumer02	YES	YES	YES	YES	YES	YES
Consumer03	YES	NO	YES	YES	YES	YES
Consumer04	NO	NO	NO	NO	NO	NO
Consumer05	NO	NO	NO	NO	NO	NO
Consumer06	YES	YES	YES	YES	YES	YES
Consumer07	YES	NO	NO	NO	NO	YES
Consumer08	YES	NO	YES	YES	YES	YES
Consumer09	YES	NO	YES	YES	YES	YES
Consumer10	YES	YES	YES	YES	YES	YES
Consumer11	YES	YES	YES	YES	YES	YES
Consumer12	YES	YES	YES	YES	YES	YES
Consumer13	YES	YES	YES	YES	YES	YES
Consumer14	YES	NO	YES	NO	NO	YES
Consumer15	NO	NO	NO	NO	NO	NO
Consumer16	NO	NO	NO	NO	NO	NO
Consumer17	YES	NO	YES	YES	YES	YES
Consumer18	YES	NO	YES	YES	YES	YES
Consumer19	YES	NO	NO	NO	NO	NO
Consumer20	YES	NO	NO	NO	NO	NO
Consumer21	NO	NO	NO	NO	NO	NO
Consumer22	NO	NO	NO	NO	NO	NO
Consumer23	NO	NO	NO	NO	NO	YES
Consumer24	YES	NO	YES	YES	NO	YES
Consumer25	YES	NO	NO	NO	NO	YES
Consumer26	NO	NO	YES	NO	NO	NO
Consumer27	YES	YES	YES	YES	YES	YES
Consumer28	YES	NO	YES	YES	NO	YES
Consumer29	YES	NO	YES	NO	NO	YES
Consumer30	YES	YES	YES	YES	YES	YES
Consumer31	YES	NO	YES	YES	YES	YES
Consumer32	YES	NO	YES	NO	NO	YES
Consumer33	NO	NO	NO	NO	NO	NO
Consumer34	YES	NO	YES	NO	NO	YES
Consumer35	NO	NO	NO	NO	NO	NO
Consumer36	YES	NO	YES	NO	NO	YES
Consumer37	YES	NO	YES	NO	NO	YES
Consumer38	YES	NO	YES	YES	YES	YES
Consumer39	NO	NO	NO	NO	NO	NO

Consumer40	YES	NO	YES	YES	YES	YES
Consumer41	YES	NO	YES	NO	NO	YES
Consumer42	YES	NO	YES	YES	YES	YES
Consumer43	YES	NO	YES	NO	NO	YES
Consumer44	YES	NO	YES	YES	YES	YES
Consumer45	YES	NO	YES	YES	YES	YES
Consumer46	NO	NO	NO	NO	NO	YES
Consumer47	NO	NO	NO	NO	NO	NO
Consumer48	NO	NO	NO	NO	NO	NO
Consumer49	YES	YES	YES	YES	YES	YES
Consumer50	YES	NO	YES	YES	YES	YES
Consumer51	YES	NO	YES	YES	YES	YES
Consumer52	NO	NO	NO	NO	NO	YES
Consumer53	YES	YES	YES	YES	YES	YES
Consumer54	NO	NO	NO	NO	NO	NO
Consumer55	YES	NO	YES	YES	YES	YES
Consumer56	YES	NO	YES	NO	NO	YES
Consumer57	YES	NO	YES	NO	NO	YES
Consumer58	NO	NO	NO	NO	NO	NO
Consumer59	YES	NO	YES	NO	NO	YES
Consumer60	NO	NO	NO	NO	NO	NO

Nature	de_1	de_2	de_3	de_4	de_5	de_6
Consumer01	NO	NO	NO	NO	NO	YES
Consumer02	YES	YES	YES	YES	YES	YES
Consumer03	YES	NO	YES	YES	YES	YES
Consumer04	NO	NO	NO	NO	NO	YES
Consumer05	NO	NO	NO	NO	NO	NO
Consumer06	YES	YES	YES	YES	YES	YES
Consumer07	NO	NO	NO	NO	NO	NO
Consumer08	YES	NO	YES	YES	YES	YES
Consumer09	YES	NO	YES	YES	YES	YES
Consumer10	YES	YES	YES	YES	YES	YES
Consumer11	YES	YES	YES	YES	YES	YES
Consumer12	YES	YES	YES	YES	YES	YES
Consumer13	YES	YES	YES	YES	YES	YES
Consumer14	YES	NO	YES	YES	YES	YES
Consumer15	NO	NO	NO	NO	NO	NO
Consumer16	NO	NO	NO	NO	NO	NO
Consumer17	NO	NO	NO	YES	YES	YES
Consumer18	NO	NO	YES	YES	YES	YES
Consumer19	NO	NO	NO	NO	NO	NO

Consumer20	NO	NO	NO	NO	NO	YES
Consumer21	NO	NO	NO	YES	YES	YES
Consumer22	NO	NO	NO	NO	NO	YES
Consumer23	NO	NO	NO	NO	NO	NO
Consumer24	NO	NO	NO	YES	NO	YES
Consumer25	NO	NO	NO	NO	YES	YES
Consumer26	NO	YES	NO	NO	NO	YES
Consumer27	YES	YES	YES	YES	YES	YES
Consumer28	YES	NO	YES	YES	YES	YES
Consumer29	YES	NO	YES	YES	YES	YES
Consumer30	YES	YES	YES	YES	YES	YES
Consumer31	YES	NO	YES	YES	YES	YES
Consumer32	NO	NO	NO	NO	NO	YES
Consumer33	NO	NO	NO	NO	NO	NO
Consumer34	YES	NO	YES	NO	YES	YES
Consumer35	NO	NO	NO	NO	NO	YES
Consumer36	YES	NO	YES	NO	NO	YES
Consumer37	YES	YES	YES	YES	YES	YES
Consumer38	YES	YES	YES	YES	YES	YES
Consumer39	NO	NO	NO	NO	NO	NO
Consumer40	YES	NO	YES	YES	YES	YES
Consumer41	YES	YES	YES	YES	YES	YES
Consumer42	YES	YES	YES	YES	YES	YES
Consumer43	NO	NO	NO	NO	NO	YES
Consumer44	YES	NO	YES	YES	YES	YES
Consumer45	YES	NO	YES	YES	YES	YES
Consumer46	NO	NO	NO	NO	NO	NO
Consumer47	NO	NO	NO	NO	NO	NO
Consumer48	NO	NO	NO	NO	NO	NO
Consumer49	YES	YES	YES	YES	YES	YES
Consumer50	YES	YES	YES	YES	YES	YES
Consumer51	YES	NO	YES	YES	YES	YES
Consumer52	NO	NO	NO	YES	YES	YES
Consumer53	YES	YES	YES	YES	YES	YES
Consumer54	NO	NO	NO	NO	NO	YES
Consumer55	YES	YES	YES	YES	YES	YES
Consumer56	YES	NO	YES	NO	YES	YES
Consumer57	YES	NO	NO	NO	NO	YES
Consumer58	NO	NO	NO	NO	NO	NO
Consumer59	YES	NO	YES	YES	NO	YES
Consumer60	NO	NO	NO	NO	NO	NO

Attractive	de_1	de_2	de_3	de_4	de_5	de_6
Consumer01	YES	NO	YES	NO	NO	NO
Consumer02	YES	YES	YES	YES	YES	YES
Consumer03	YES	YES	YES	YES	YES	YES
Consumer04	YES	NO	YES	NO	NO	NO
Consumer05	YES	NO	YES	YES	NO	YES
Consumer06	YES	YES	YES	YES	YES	YES
Consumer07	YES	NO	NO	NO	NO	NO
Consumer08	YES	NO	YES	YES	YES	YES
Consumer09	YES	YES	YES	YES	YES	YES
Consumer10	YES	YES	YES	YES	YES	YES
Consumer11	YES	YES	YES	YES	YES	YES
Consumer12	YES	YES	YES	YES	YES	YES
Consumer13	YES	YES	YES	YES	YES	YES
Consumer14	YES	NO	YES	YES	NO	YES
Consumer15	YES	NO	NO	NO	NO	NO
Consumer16	YES	NO	NO	NO	NO	NO
Consumer17	YES	NO	YES	YES	NO	NO
Consumer18	YES	NO	YES	YES	YES	YES
Consumer19	YES	NO	YES	NO	NO	NO
Consumer20	YES	NO	NO	YES	NO	NO
Consumer21	YES	NO	YES	YES	NO	NO
Consumer22	YES	NO	YES	YES	NO	YES
Consumer23	YES	YES	YES	YES	NO	YES
Consumer24	YES	YES	YES	YES	NO	YES
Consumer25	YES	YES	YES	YES	NO	YES
Consumer26	YES	NO	YES	NO	NO	NO
Consumer27	YES	YES	YES	YES	YES	YES
Consumer28	YES	NO	YES	YES	NO	YES
Consumer29	YES	NO	YES	YES	NO	YES
Consumer30	YES	YES	YES	YES	YES	YES
Consumer31	YES	YES	YES	YES	YES	YES
Consumer32	YES	NO	YES	YES	NO	NO
Consumer33	YES	NO	NO	NO	NO	NO
Consumer34	YES	NO	YES	YES	NO	NO
Consumer35	YES	NO	YES	YES	NO	NO
Consumer36	YES	NO	YES	YES	NO	YES
Consumer37	YES	NO	YES	YES	NO	YES
Consumer38	YES	YES	YES	YES	NO	YES
Consumer39	YES	NO	NO	NO	NO	NO
Consumer40	YES	NO	YES	YES	NO	YES
Consumer41	YES	NO	YES	YES	NO	YES
Consumer42	YES	YES	YES	YES	NO	YES

Consumer43	YES	NO	YES	YES	NO	NO
Consumer44	YES	NO	YES	YES	NO	YES
Consumer45	YES	YES	YES	YES	YES	YES
Consumer46	YES	YES	YES	YES	NO	YES
Consumer47	NO	NO	NO	NO	NO	NO
Consumer48	NO	NO	NO	NO	NO	NO
Consumer49	YES	YES	YES	YES	YES	YES
Consumer50	YES	NO	YES	YES	YES	YES
Consumer51	YES	YES	YES	YES	YES	YES
Consumer52	YES	NO	YES	YES	NO	YES
Consumer53	YES	YES	YES	YES	YES	YES
Consumer54	YES	NO	NO	YES	NO	NO
Consumer55	YES	YES	YES	YES	YES	YES
Consumer56	YES	NO	YES	YES	NO	YES
Consumer57	YES	NO	YES	YES	NO	YES
Consumer58	YES	NO	NO	NO	NO	NO
Consumer59	YES	NO	YES	YES	NO	NO
Consumer60	YES	NO	NO	NO	NO	NO