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Study on relations between visual and haptic perceptions of textile products

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Abstract

Today, the rapid development of Internet has generated a huge revolution in people's way of consumption. Online shopping is becoming ever more attractive for general public due to its economical and convenient features. During online transactions of textile products, the digitalized interactive platform makes the purchasing as simple as a click, but in the same time it sets a limit to some of our real desires about a fabric such as touch. So far, many researchers have attempted to provide consumers with a real sense of fabric hand through virtual experiences. One remarkable step forward is the development of force feed-back devices. But due to the simulation difficulties and the intuitive deficiencies of mechanical measurement, till now, the progress in the direction is still far from satisfactory.

In the current thesis, we propose for the first time a systematic methodology to study fabric tactile properties through visual perceptions. First of all, we investigate the physiological and cognitive basis of visual and haptic perceptions of fabric tactile properties. Next, we propose a fundamental hypothesis that fabric tactile properties can be, to a big extent, interpreted through our eyes. In order to verify this hypothesis, sensory experiments are carried out on a number of textile products in video, image and real-touch scenarios. A novel approach based on the concept of inclusion degree is developed to study the relations between the tactile data obtained from different sensory modalities. From this study, we conclude that it is possible to perceive fabric tactile properties through visual representations, which confirms the previously proposed hypothesis. On this basis, in order to further explore the visual interpretative mechanism, new sensory experiments are organized to evaluate samples' visual features and tactile properties, respectively. The previously proposed mathematical approach is modified to be able to measure multiple-to-single relations so as to extract for each tactile property a set of relevant visual features on it. Finally, a fuzzy neural network (Adaptive network-based fuzzy inference system, in short ANFIS) is developed to model the obtained interpretative relationships. After being compared with conventional statistical methods, which are frequently used to study relations of sensory data, the proposed approach is proved to be more robust and easier for result interpretation. It is also more efficient in dealing with sensory data with high uncertainty and imprecision related to a small number of available samples.

Key words: Fabric tactile properties, Haptic perception, Visual perception, Associative memory, Approximate reasoning, Rough sets, Inclusion degree, Fuzzy sets, Fuzzy inference, Adaptive network-based fuzzy inference system

Etude de relations entre les perceptions visuelles et haptiques des produits textiles

Résumé

Aujourd'hui, le développement rapide de l'Internet entraîne une grande révolution dans notre mode de consommation. Les achats en ligne sont de plus en plus attractifs pour le grand public en raison du coût économique faible et de la grande facilité d'accès aux informations, aux avis et aux comparaisons sur les produits. Au cours des transactions en ligne de produits textiles, la plate-forme numérisée interactive permet l'achat d'un simple clic de souris. Mais dans le même temps, il fixe une limite physique à certains de nos désirs réels, en particulier sur les étoffes pour un sens comme le toucher. Jusqu'à présent, de nombreux chercheurs ont tenté d'offrir aux consommateurs une véritable sensation du toucher de tissu à travers des expériences virtuelles. Un progrès remarquable s'est fait jour avec le développement des périphériques à retour de force. Mais en raison des difficultés liées à la simulation informatique et l'interprétation des mesures mécaniques, jusqu'à aujourd'hui, les progrès selon cette orientation sont encore loin d'être satisfaisant.

Pour ces travaux de thèse, nous proposons pour la première fois une méthodologie systématique pour étudier les propriétés tactiles de tissu au travers de perceptions visuelles. Tout d'abord, nous étudions les bases physiologiques et cognitives des perceptions visuelles et haptiques des propriétés tactiles des tissus. Ensuite, une hypothèse fondamentale est proposée pour que les propriétés tactiles des tissus puissent être interprétées à travers nos yeux. Afin de vérifier cette hypothèse, des expériences sensorielles ont été conduites sur un nombre important de produits textiles selon trois différents scénarii : vidéo, image et toucher réel. Une nouvelle approche basée sur le concept de degré d'inclusion est développée pour étudier les relations entre les données tactiles obtenues à partir des différentes modalités sensorielles. De cette manière, nous concluons qu'il est tout à fait possible de percevoir les propriétés tactiles des tissus à travers des représentations visuelles. Ceci confirme l'hypothèse proposée précédemment. En nous appuyant sur ces résultats, afin d'explorer le mécanisme interprétatif de la vision, nous effectuons de nouvelles expériences sensorielles, permettant d'évaluer respectivement les caractéristiques visuelles et les propriétés tactiles des échantillons. Ensuite, nous modifions l'approche mathématique proposée précédemment afin de mesurer les relations de type un à plusieurs, de manière à extraire pour chaque propriété tactile d'un ensemble de caractéristiques visuelles les plus pertinentes. Enfin, ANFIS (un réseau neuronal combinant les techniques floues) est utilisé pour modéliser et interpréter quantitativement ces relations. Après une comparaison avec les méthodes statistiques classiques, fréquemment utilisées dans l'analyse des relations des données sensorielles, nous constatons que l'approche proposée est plus robuste et plus facile pour interpréter les résultats. Il est aussi plus performant dans le traitement de l'incertitude et de l'imprécision des données sensorielles, liées au nombre faible d'échantillons disponibles.

Mots clés : Propriétés tactiles de tissu, Perception haptique, Perception visuelle, Mémoire associative, Raisonnement approximatif, Ensembles rugueux, Degré d'inclusion, Ensembles flous, Inférence floue, Réseau adaptatif –basé sur système d'inférence floue

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GENERAL INTRODUCTION

Today, with rapid development of information technology, the way of consumption has changed significantly. Especially, e-shopping has become more and more favorable for general public due to its economic and convenient features. In practice, purchasing textile products constitutes one of the most important aspects in e-shopping. However, one big technical barrier preventing the development of textile/garment e-shopping is the products' intangibility during transactions.

Much research in recent years has focused on investigating the possibility of providing a user with a completely reliable sense of fabrics through a virtual experience. One remarkable progress in this field is the development of many haptic force feedback devices, such as the Cyberglove (from virtual technologies.inc, US), the PHANTom (from TiNi Alloy, US), and more recently, the HAPTEX system (from Miralab, Switzerland), etc. However, the available haptic systems do not have the sensitivity required for an accurate simulation of fabric hand. Most of them can only perform basic simulation tasks whose accuracy is far from reaching the market. Moreover, the attempts made by these devices are based on objective measurements of physical properties on real fabrics. But, so far, there is not a commonly acceptable FOM (Fabric Objective Measurement) that is capable of comprehensively quantifying people's complicated sense of touch.

Classically, 'fabric hand' was defined by the Textile Institute in 1975 as 'subjective assessment of a textile material obtained from the sense of touch.' Besides, as was stated by Fritz, 'people are capable of making objective, quantitative, and repeatable assessments of their sensations'. It is believed that the most effective way to study fabric hand should be from the perspective of human's natural perception. And for this reason, fabric hand has been extensively studied using sensory analysis. One commonly used sensory method is descriptive analysis, or profiling analysis, which is aimed at measuring sensory differences among a set of products through quantification of well-defined attributes. A lot of work has been dedicated to well adopting these techniques in the study of fabric hand.

Visual evaluation is another important aspect of textiles' sensory study. A big number of papers have been found in the aesthetic and behavioral studies on the color and the structural appearance of textile products. Some researches deal with the quantification of garment visual information. However, in all these fields, few studies have tried to explore fabrics' tactile properties from perceived visual information.

Actually, according to many previous studies on human neuropsychology and cognitive psychology, most of the tactile information in our daily life can be interpreted through human's visual perception, which is in accordance with our real-life experience. It is studied that our brain has a very sophisticated memory association mechanism permitting us to perceive the outside world in a multi-channel mode. For example, when we touch a fabric, its tactile information will be associated with the synchronized visual features and memorized simultaneously in our brain so as to create a so-called memory association. After this experience being repeated for a sufficient number of times in our daily contact, the memory association established between the tactile and visual perceptions of this fabric can be gradually strengthened. In this way, when we see or even just visualize this object again, the related tactile information will be recalled from the memory association.

On this premise, we are considering the possibility to identify the cooperative and compensatory mechanism between the multisensory information of textile products (i.e. the tactile and visual perceptions), so as to provide our customers with the most close-to-teal sense of fabric hand in a remote or virtualized environment (online shop, for instance).

In this PhD research project, we proposed a systematic approach to investigate the relations between visual and haptic perceptions on the tactile properties of textile products. At the experimental level, sensory evaluations were standardized and carried out on a number of flared skirts made of typical fabric materials.

With regards to data analysis, in the first place, we attempted to explore the extent to which fabrics' tactile properties could be interpreted through specific visual displays. The mathematical methodology comes from the ideas of both fuzzy sets and rough sets theories. The inclusion degree from rough sets theory was applied as a basis to measure the classification consistency between the perceived tactile information about the samples obtained from different sensory modalities. Then, a fuzzy set approach was employed to modify this measure by quantifying the vagueness of sensory observations so as to make it better adapt to the current sensory problem characterized by a lot of uncertainty and imprecision. On the other hand, the ordinal correlation between different sensory data was examined using a non-parametric method, Kendall's coefficient. Finally, in order to create a reasonable integration of the previous two indices, a general consistency measure was constructed by introducing the expert knowledge into a fuzzy inference system. As compared with classical methods, e.g. PCA, Multidimensional scaling, Multiple factor analysis and various kinds of correlation coefficient analysis, etc., the novel approach is believed to be competent in (1) solving nonlinear problems, (2) dealing with both numerical and linguistic data, (3) modeling human expert reasoning so as to produce precise and straightforward interpretation of results, and (4) computing with relatively small sets of data and without need of any preliminary or additional information like probabilistic distributions in statistics. After applying this approach, a significant conclusion has been drawn that most of the tactile information can be perceived correctly by assessors through either video or image displays, while a better performance is detected in video scenarios.

On the above basis, the next important step of the thesis was to investigate the interactive mechanism between the two perceptual modalities (visual and haptic). The method used in the previous step was modified here to extract principal visual features for each fabric tactile property. And then, each pair of multiple-to-single relation was modeled using a fuzzy neural network (ANFIS).

Our study has put forward a new and efficient way to investigate the relations between visual and haptic perceptions of fabrics' tactile properties, and has confirmed the possibility of acquiring tactile information through the visual representations of textile products in a non-haptic environment. Our work is expected to be a significant step forward on the way of enhancing customers' virtual-reality experience of textile products. Its major contributions as well as its perspectives are summarized as follows. Firstly, the combination of our approach and feature abstraction techniques will enable us to interpret fabric tactile information by extracting and analyzing products' visual features or elements from their visual representations (e.g. images, videos or even virtualized displays) so as to provide our customers with the most close-to-real experience of the textile products in a virtualized environment. Secondly, on the platform of virtual-reality interaction, the information can be flowing not only from manufacturers to customers, but also from customers back to manufacturers. For example, customers' preference on fabric hand as feedbacks would be a guidance helping manufacturers to develop their product design as well as visual representations.

Just imagine, in the very near future, when you enter an online apparel store, you can find the items according to your preference on the color, style or decoration. Then you put on the item in the virtual fitting room assessing its physical fitness and dynamic performance. And finally, by a simple click, you can have access to a detailed description of the tactile information about the selected apparel item. So simple and it is achievable.

State of the art (Chapter 1)

The essence of the thesis is to analyze people's perceptions about textile products. Thus, in the first chapter, we present the key background of the thesis, in which two major points are concerned. Firstly, we give a general introduction to the physiological basis of human senses and their correlations with textile evaluation. An emphasis is put on the discussion on the two principal senses, touch and vision. Secondly, we introduce the definition and basic principles of sensory evaluation as a discipline and a review work has been done on the research background about the sensory analysis of textile products. Finally, the standpoint and general scheme of the current study is given.

Hypothetical discussion on multisensory perception of fabric tactile properties (Chapter 2)

In this chapter, we focus on the discussion of the possibility of interpreting fabric tactile properties through vision from the perspective of physiological and cognitive psychology. Initially, we present the definition of fabric tactile property or fabric hand. Intuitively, fabric hand is a haptic term. So, in the next part, we introduce in detail the physiological basis of human haptic perception. After that, we come to the most important part of this chapter, that is, the visual perception of fabric tactile properties. Accordingly, an introduction is given on the physiological basis of human visual perception. Then, a profound discussion is carried out on the possibility of visual perception of various tactile properties of textile products from the perspectives of psychology and cognitive memory, respectively. In this chapter, an important hypothesis, which constitutes the theoretical premise of our proposed methodology in the current study, is proposed that fabrics' tactile properties could be, to a big extent, perceived through our eyes.

Computational techniques (Chapter 3)

For formalizing and modeling human perception data, we propose a systematic approach combining the use of inclusion degree from rough sets theory, fuzzy techniques, and fuzzy neural network (ANFIS). So, in this part, we first introduce the concepts of approximate reasoning, rough sets, rough mereology and inclusion degree. Then, the notion of fuzzy sets, fuzzy membership functions, and the related operations and fuzzy inference are explained. Finally, the development of a fuzzy neural network, ANFIS, is described to model multiple-to-single relations.

Visual interpretability of fabric tactile properties (Experiment I) (Chapter 4)

In this chapter, we are aimed to verify the visual interpretability of fabric tactile properties. Tactile evaluation experiments are carried out by a panel of experts, on a number of textile fabrics made into flared skirts, in video, image and real-touch scenarios. Using the techniques presented in Chapter 3, we put forward our approach for studying the relations between the tactile data obtained from different sensory modalities. This approach is based on the application of inclusion degree and fuzzy techniques, and is proved to be capable of solving sensory problems of high uncertainty and imprecision after being compared with classical linear correlation method. The results obtained from Experiment I confirm that most tactile information of a textile product can be transmitted through its visual representations.

Interpretative mechanism of visual perception of fabric tactile properties (Experiment II) (Chapter 5)

On the basis of the study in Chapter 4, we are going to further investigate how fabric tactile properties can be interpreted through samples' visual representations. A new round of sensory experiments with the addition of another twelve fabric samples are carried out in two scenarios, visual feature evaluation and tactile evaluation, respectively. The mathematical approach proposed in previous chapter is modified to adapt to measuring multiple-to-single relations between fabric tactile properties and several visual features which resemble the multisensory cooperation in real life experience. After applying this approach to the sensory data obtained from Experiment II, for each tactile property, a set of principal visual features can be extracted. Finally, a fuzzy neural network, ANFIS, is developed to model the relationships obtained from the previous step. Till then, the interpretation of fabric tactile properties through visual perceptions is accomplished. Then, our research has come to the conclusive point that it is possible to interpret fabric tactile information from the visual perceptions of the corresponding textile item, which is significant for enriching customers' purchasing experience in virtual environment, while, at the same time, is of instructive importance for the manufacturers to integrate customers' tactile preference into the product design as well as the corresponding visual displays.

CHAPTER 1: State of the art

Our research is carried out around human being's perceptions about textile products. Human senses are to our perception as instruments are to the physical measurement. So, as the fundamental part of the whole study, this chapter first introduces some basic notions about human sensory systems including the sensory receptors and the general sensory pathways for the perception of external stimulus. Then the relations between human perceptions and textile products are discussed with an emphasis on the two principal senses, touch and vision.

Making judgments upon the perceived information is an important human mental activity which can reveal one's perceptual level about the external stimulus, being a certain people, object or event. In our research, subjects' perceptions on the samples obtained from different sensory modalities (i.e. tactile and visual modalities) are measured and analyzed according to the methodology originated from the theory of sensory analysis or sensory evaluation. So, as another important part of this chapter, an introduction has been done on the definition, principals and development of sensory analysis as well as some research progress with respect to the sensory analysis of textile products.

Finally, this chapter ends with a general schema according to which the whole study is to be carried out. Some basic ideas about the sensory methods as well as the mathematical approaches to be employed are mentioned here.

1.1 Human perceptions and textile products

We experience reality through our senses. The senses and their operation, classification, and theory are overlapping topics studied by a variety of fields, most notably neuroscience, cognitive psychology and philosophy of perception. There is no firm agreement among neurologists as to the number of senses because of differing definitions of what constitutes a sense. One definition states that a sense is a faculty by which outside or inside stimuli are perceived [GELDARD, 1953].

The terms that need to be defined and distinguished are sensation and perception. Sensation is considered to involve all those processes that are necessary for the basic detection of the outside world. For example, a sensory process might be detecting the loudness of a sound or the type of taste in a food. Perception identifies and interprets this sensory information. So the sound becomes a cat's purr and the food becomes a well prepared steak. Thus, we can say that, sensation is the physiological methods of perception [WYBURN, 1964].

As the first part of this section, a brief introduction of human senses with its importance in textile evaluation has been presented.

1.1.1 Human perceptions

A sensory system is a part of the nervous system responsible for processing sensory information. A sensory system consists of sensory receptors, neural pathways, and parts of the brain involved in sensory perception.

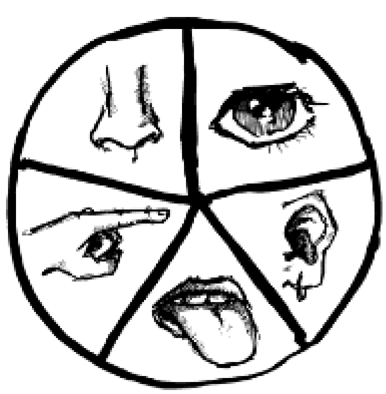


Figure 1 - 1 Human senses

1.1.1.1 Sensory receptors

Sensory receptors are sensory nerve endings that respond to stimuli in the internal or external environment or organism. They exist extensively in the skin, muscles and various organs of our body to help us feel the world as well as ourselves. Generally, the sensory receptors of human beings are split into two different groups according to the location of the stimulation, the exteroceptors and the ineroceptors, respectively. The exteroceptors detect stimulation from the outside of our body, such as smell, taste and equilibrium, while the interoceptors receive stimulation from the inside of the body. For instance, blood pressure dropping, changes in the glucose and pH levels.

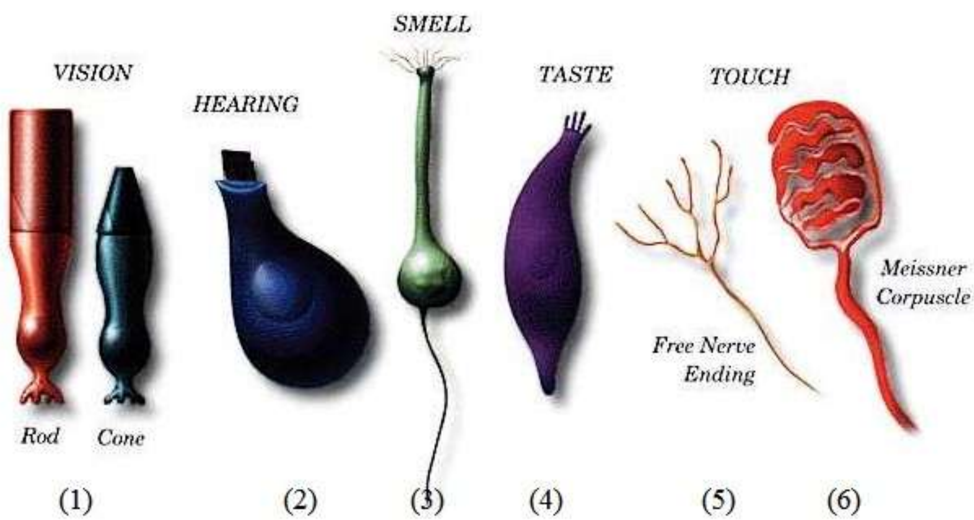


Figure 1 - 2 Receptors for different sensations

((1) rod and cone cells of the retina are specialized to respond to electromagnetic radiation of light; (2) the ear's receptor neurons are topped by hair bundles that move in response to the vibrations of sound; (3) olfactory neurons at the back of the nose respond to odorant chemicals; (4) taste receptors on the tongue and back of the mouth respond to chemical substances; (5) free nerve endings bring sensations of pain; (6) tactile (or Meissner's) corpuscles are specialized for response to fine touch, pressure and low-frequence vibration.)

It is commonly recognized that human beings have at least five basic senses, touch (somatic sense), vision, hearing, taste and olfaction (smell), respectively (Figure 1-1) [GELDARD, 1953]. Certain receptors are sensitive to certain types of stimuli. Thus, according to the type of the stimuli, the sensory receptors can be classified into five groups. Mechanoreceptors detect the deformation caused by force, such as touch, pressure, vibration, stretch and so on. Thermoreceptors sense changes in temperature. Photoreceptors receive information related to light energy. Chemoreceptors get stimulated by the chemicals in solution, such as smell, taste, blood chemistry and so on. And nociceptors help our body feel the pain. Figure 1-2 illustrates the major receptors and the corresponding functions for different sensations.

1.1.1.2 Sensory pathway

A general sensory pathway extends from the point where the stimulus is received to the specialized processing region in the brain [STOPFORD, 1930]; [COREN, 2003]. But our brain never receives stimulation directly from the outside world. For example, the brain's experience of an apple is not the same as the apple itself. It must always rely on secondhand information from the go-between sensory system, which delivers only a coded neural message, out of which the brain must create its own experience.

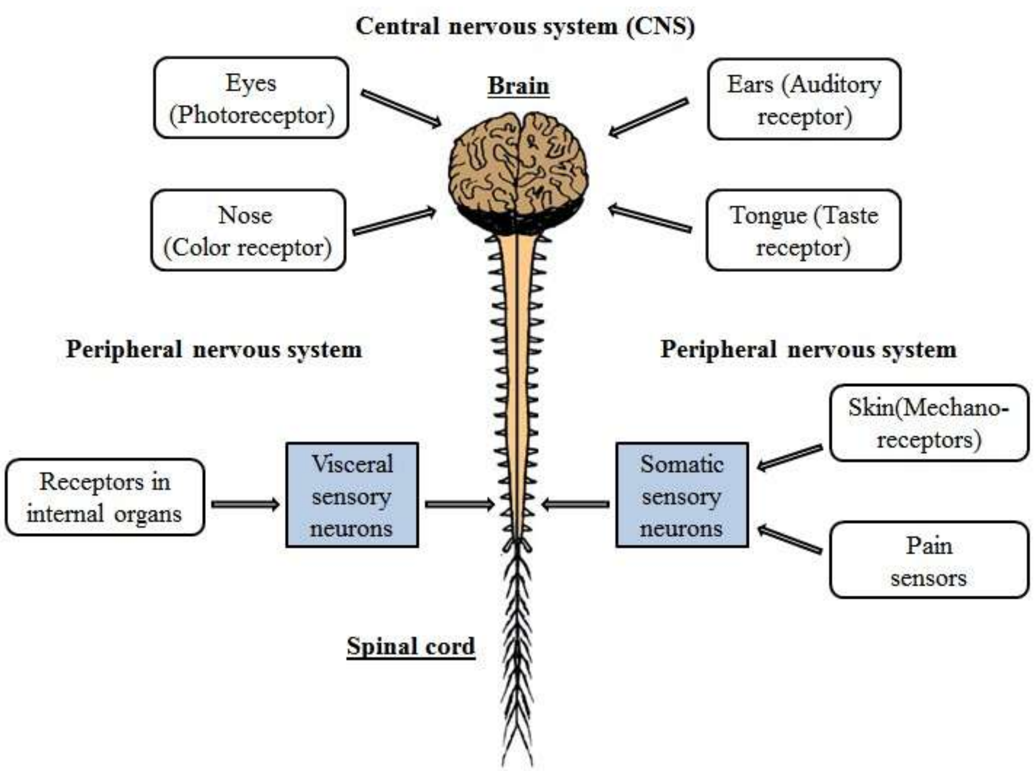


Figure 1 - 3 A highly schematic diagram of human sensory system

As the first component of a sensory system, it is the job of the sensory receptors to convert or transduce incoming physical or chemical stimuli into changes in the electrical potentials or "action potentials" – the only language the brain understands. And this process is called sensory transduction. The action potentials produced by the receptors will, then, conduct to the spinal cord and brain, which constitute the so-called Central nervous system (CNS), for processing and interpretation. What is worth mentioning is that the message that is sent to the CNS is always a train of action potentials, or called nerve impulses, regardless of the kind of stimulus that excites a particular receptor. Figure 1-3 shows a highly schematic diagram of human sensory system [LODISH, 2000].

Take vision as an example. For a visual stimulation to become meaning perception for the human brain, it must undergo several transformations [HUBEL, 1979]; [HEEGER, 1999]. First, physical stimulation (light waves from the object, i.e. the butterfly) is transduced by the eyes, where information about the wavelength and intensity of the light is coded into neural signals (or nerve impulses). Second, the neural messages travel to the sensory cortex of the brain, where they become sensations of color, brightness, form, and movement. Finally, the process of perception interprets these sensations by making connections with memories, emotions and motives in other parts of the brain. Figure 1-4 is a brief illustration about the sensory process of the visual perception. Similar processes operate on the information taken in by other senses.

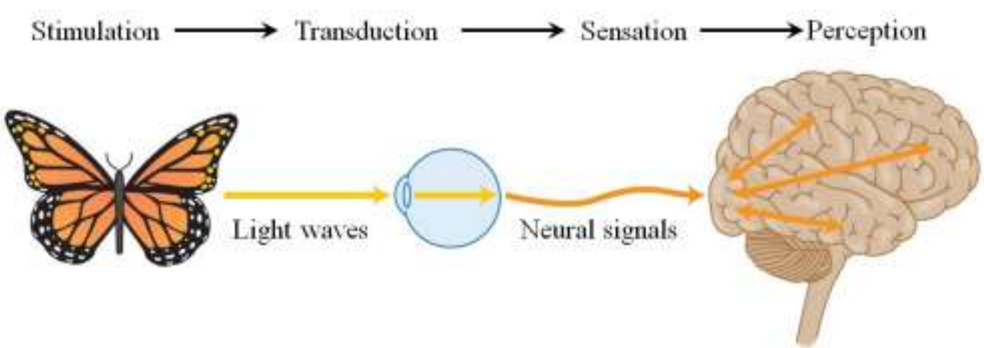


Figure 1 - 4 From stimulation to perception (on vision)

1.1.1.3 Functional areas of brain

As was illustrated above, our brain plays a very important role in the whole process of perception. The neural signals triggered by the receptors travel through the specialized sensory pathways and finally reach here, the Grand central station, to be mapped and interpreted into a structure of awareness and reality.

The cerebral (the adjective form of cerebrum which is the anatomical term of brain) hemisphere is covered with a thin layer of gray matter called the “Cerebral cortex”. This thin (about 1.5mm to 5mm in thickness) layer of tissue contains over one billion neural cell bodies (soma) and is highly convoluted or folded. The cerebral cortex is the most developed region of the brain. Its function involves processes like thinking, perceiving, processing and understanding languages [ROLAND. 1998]; [VAN ESSEN, 1998].

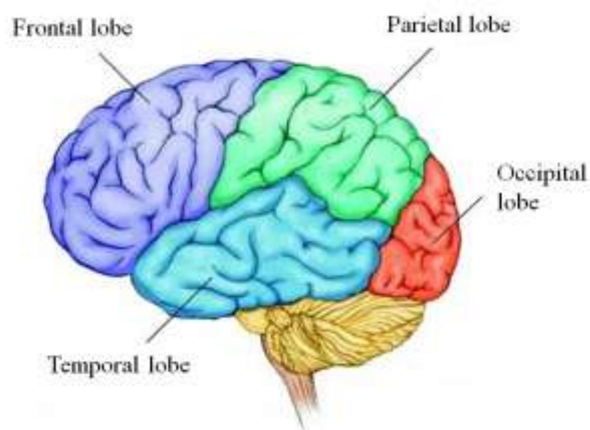


Figure 1 - 5 Cerebral cortex lobes (left hemisphere)

Figure 1-5 is a lateral view of the cerebral cortex (left hemisphere). There are four cerebral cortex lobes; frontal lobe, parietal lobe, temporal lobe and occipital lobe, respectively. They are separated by shallow grooves called sulci. The frontal lobe location is anterior to parietal lobe which is in turn anterior to the occipital lobe. The lateral part of the cerebral hemisphere is the temporal lobe.

It is known that no area of the brain functions alone, although major functions of various parts of the lobes have been determined. The functional areas of the cerebral cortex (lateral view of the left hemisphere) are shown in Figure 1-6. For example, the motor areas are responsible for generating impulses which innervate all effectors in the body, e.g., voluntary skeletal muscles, involuntary muscles, and glands, both endocrine and exocrine. The Wernicke’s area (the area outlined by dashes on the right of the figure) is involved in the understanding of written and spoken language. But these areas are not to be concerned in the current study.

We are interested in the functional areas related to sensory processing which is illustrated on the left part of Figure 1-6. On each lobe locate primary sensory areas and association areas which are responsible for processing various sensory inputs. The primary sensory areas receive and interpret sensory impulses, e.g., olfaction in the frontal lobe, tactile sensations in the parietal lobe, visual sensations in the occipital lobe, taste, hearing, and equilibrium in the temporal lobe. The association areas located in the surrounding of the primary sensory areas are involved in integrating sensory information with emotional states, memories, learning and rational thought processes. For example, when we hear a song coming from a distance, firstly, the sound wave would be received by the auditory receptors in the ears and transduced into neural signals. The signals would then travel through the specific pathway to the auditory reflex center of the midbrain, the thalamus and then the primary auditory area in the temporal lobe of the cerebral cortex where the neural signals would be interpreted and restored as melodies which is the process of sensation. Finally, in the help of the association area connected to the primary auditory part, our brain can recognize it as an old song, and at the same time, the name, singer and even the related personal story would be recalled. And till now, the whole process of perception is completed.

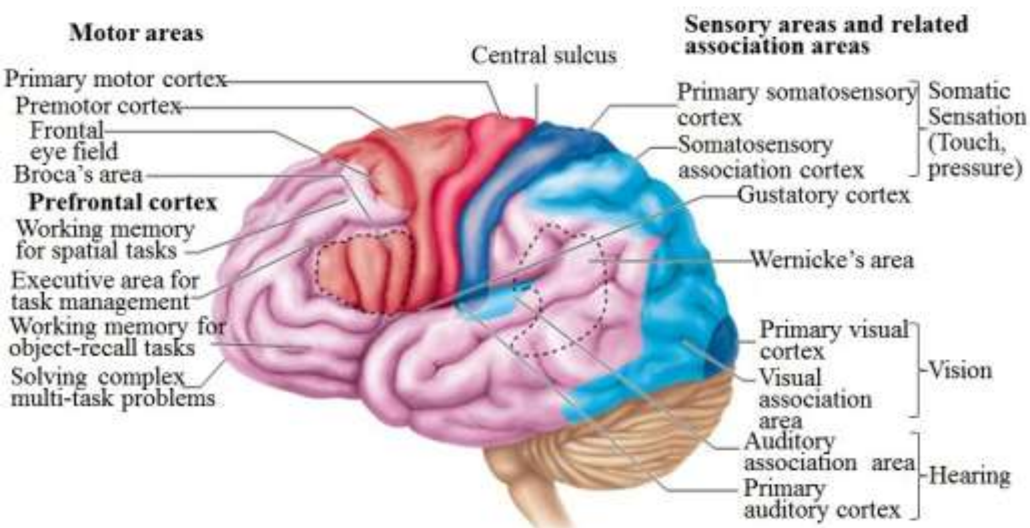


Figure 1 - 6 Functional areas of the cerebral cortex

1.1.2 Perceptions of textile products

As we all know, textile products are a kind of sensory goods. Before making a purchase, customers tend to have an all-around evaluation of the apparel item. Taking a lady's jacket as an example, its color, style, try-on fitness and fabric texture are important elements greatly influencing customers' purchasing decision. In recent years, as the competition in the textile and apparel industries is becoming increasingly fiercer, manufacturers are making more investment than ever in integrating customers' sensory preference into the development of their products. Accordingly, in the research field, lots of effort has been dedicated to the sensory study of textile products.

Two kinds of human senses, vision and touch, are involved in the above example. Actually, they are the most often used senses during our evaluation of textile products. By vision and touch, we can get access to most of the information we desire from an apparel item such as the aspects concerning the aesthetics (e.g., color, style and decoration of the clothes) and comfort (fitness of the clothes and tactile texture of the fabric, etc.). Thus, in an apparel store, clothes are displayed in such a way that we can easily observe their appearance and touch the fabric during purchasing.

1.1.2.1 Touch

Touch is considered as the most direct and concrete contact we can make with the real world. It is believed that a tangible environment will provide the blind people with more sense of safety. To be able to touch is our basic need in order to know something in the surrounding. So, as regards to textile products, since they have closest and sometimes direct interaction (e.g., underwear items) with our body, their touching or tactile properties are very important and are directly related to our sense of comfort. A generalized concept of touching experience of an apparel item has three folds; (a) the pressure felt on the skin when we wear the clothes and make various motions. This sensory experience comes from the structure of the clothes and the elasticity of the corresponding fabric. For example, a tightly tailored jacket made of non-elastic material tends to make one feel pressured on the covered area during wearing. (In the context of the current study, only the fabric elements are concerned); (b) the textures or surface properties sensed when the fabric moves on our skin during wearing. "Rough", "slippery" "prickly", "fuzzy", etc. are often used descriptors of this kind; (c) the temperature felt when the fabric is touched by our skin. It is studied that the sensed temperature of a fabric is related to the fabric's surface state. For example, a surface with lots of fluff like the corduroy is generally believed to be warm to touch, while a slippery surface like the silk tends to give us a refreshingly cool feeling.

1.1.2.2 Vision

It is believed that over eighty percent of our knowledge about the outside world is acquired by our eyes. [WANG, 2001] There is a saying, 'seeing is believing', which reflects human's strong dependency on the visual information. The receptive field of vision is quite comprehensive. For example, at the macro-level, our eyes can receive information concerning the coloring, size, shape and spatial position of an object. On the other hand, at the micro-level, by vision we can also recognize the fine structural details of a surface.

So, with regards to textile products, according to the type of the stimuli, the information which can be perceived by vision, or called visual features / elements, is divided into two groups. The first group is called 'macro features' which includes the large-scale macrostructures of apparel items. Taking a lady's summer blouse as an example, the macro features include its colors, silhouette, detail decorations, pleats, and even the stitching shape. The other group is called 'micro features' which corresponds to the microstructures of the fabric surface such as 'roughness', 'stiffness', 'fuzziness' and so on. The former group is easy to understand, since these features are generally considered as vision-dominated. But for the latter one, its mechanism is not commonly recognized. Although, as was mentioned previously, the micro features or textures of a fabric are generally taken as a kind of haptic properties which are often perceived by hand exploration, the perception of texture is not limited to touch. While any definition of texture will designate it as a surface property, as distinguished from the geometry of an object as a whole, beyond this point of consensus there is little agreement as to what constitutes texture. Indeed, the definition of texture will vary with the sensory system that transduces the surface. As for the fabrics, their surface characteristics or textures originate from the weave, yarn thickness, yarn density and so on. Actually, these parameters can be seized by our eyes via diffusely reflected light which comes from (1) at the surface layer of fibres and (2) between surfaces of internal fibres. As we view a real textile sample, the light reflected diffusely stimulates our eyes and provides two-dimensional color images on our retinas as an image of the woven construction, at which point our brain registers a three-dimensional image by way of recognizing memories of experiences with fabrics. And on this basis, further judgments, like 'a bit rough', 'quite fuzzy' and so on, will be made by the subject [LEE, 2001].

Wearing is a process combining the wearer's static and dynamic requirements on the textile product. The quality of an apparel item, no matter what it concerns, e.g. the aesthetic aspects (colors, styles, etc.) the tailoring fitness, the physical and thermal comfort of the textile material, or the fabric surface texture, will be revealed during different wearing occasions such as standing or sitting still in the office, walking on the street or even doing outdoor sports. In this sense, the visual features about a textile product can be classified according to the type of representation into two major categories, static features and dynamic features, respectively. Taking a summer skirt as an example, the static features include its color, silhouette, drape, pleat size and shape, surface textures and so on. On the other hand, the dynamic features of the skirt can be its swinging range, ethereality, clinging effect, etc. during walking.

In fact, our eyes can perceive much more information about a textile product than those above. Due to the extensive receptive field of vision, and human being’s strong capacity in memory association, we can ‘see’ some stimulation which is conventionally believed to be only accessible by other sensory modalities. [ASCHOEKE, 2012]; [ANDERSONS, 1980]For example, sometimes, when we view a dress displayed in the window, even if we don't touch it, its fabric tactile properties such as the softness, stretchiness and so on can still be assumed correctly by us. According to some research in cognitive psychology, the cross-modal interaction between vision and touch is especially common in our daily life. And this is also what we aim to deal with in the current study that whether and how the fabric tactile properties can be interpreted through visual perceptions. More detailed discussion on the so-called memory association will be presented in Chapter 2.

1.1.2.3 Other senses

Apart from touch and vision, other human senses such as hearing and smelling also have their places in the sensory evaluation of textile products (Figure 1-7). The frictional sound of fabric is generated when a fabric is rubbed against another. [DAVID, 1986]This sound can be pleasant like the rustling sound of the silk, but also can be annoying like the harsh sound of a coated fabric. Taking the coated fabrics used for a waterproof jacket as an example, they tend to make a lot of noise, which sometimes bothers not only the wearers but also people surrounded. In recent years, many researches have been carried out on the acoustic properties of textile products to meet consumers’ ever increasing demand in clothing comfort. The research directions include fabric noise analysis on specific materials, study on physiological responses to fabric sounds, and modeling of relationships between sound parameters and mechanical properties of fabrics, etc. [NA, 2003];[YI, 2000];[YI, 2002]

Although fabric odour does not seem to be as influential as touch and vision in the handle and quality assessment, some fabrics do have characteristic odours, which signal their authenticity and quality for specific end-uses. In domestic laundering, the effective removal of body odours, smoke and cooking smells from textiles, followed by the delivery of long-lasting fragrances from detergent products and rinse conditioners, is of considerable importance. [BISHOP, 1995][WANG, 2005]

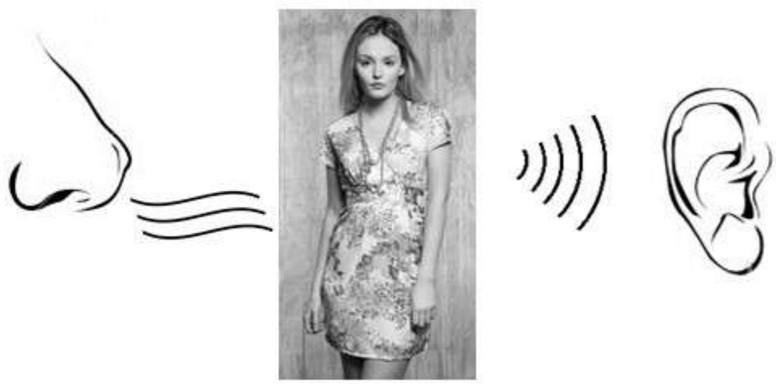


Figure 1 - 7 ‘Smelling’ and ‘hearing’ the clothes

1.2 Sensory analysis

It is widely recognized that data acquisition is the foundation of any research work. Our current study deals with multisensory information about textile products which is identified as subjective data. (It is worth mentioning that the word ‘subjective’ labels the type of data obtained from human, which is in contrast to the ‘objective’ data acquired from instrumental measurement. However, with regards to the acquisition and analysis of the data, there is a trend to use the description of ‘sensory analysis’ to replace the ‘subjective analysis’, since nowadays more and more quantification techniques have been employed to collect and process human data.) As compared with objective data, sensory data are considered as uncertain and imprecise. In this situation, it is especially important to have a standardized and systematic research method to extract reliable results from sensory data.

In this part, we will give an introduction to the so-called sensory analysis as a new methodology communicating product development with human perceptions, with its application to textile products. The following discussion will be carried out around the definition and industrial application of sensory analysis, sensory data acquisition (e.g. sensory experiments) and modeling of sensory relations.

1.2.1 Definition and industrial application

Sensory analysis or sensory evaluation is a newly emerged discipline which was developed since the 1970s, and was initially applied to food industry [SSHA, 1998]; [BLUMENTHAL, 2001]. In 1975, the Sensory Evaluation division of the Institute of Food Technologists [DIJKSTERHUIS, 1997] gave the definition of sensory analysis (or evaluation) which has been commonly accepted now:

Sensory analysis is 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.

Nowadays, sensory analysis has been applied to many other industrial fields, such as cosmetics, automobiles and textiles [BISHOP, 1996]; [GRABISCH, 1997]; [XUE,2009]; [GIBOREAU, 2001]; [LODEN, 1992]; [BACLE, 2001]. This approach has become a competitive method for the development of new industrial products. The major objectives of sensory analysis in industrial application can be summarized as follows.

(1) To improve the quality control of the products for which instrumental measurement is difficult or expensive;
(2) To monitor the production;
(3) To develop new products through market study (i.e., collecting and analyzing consumers' preference).

Today, the approach of sensory analysis has been largely employed by various industries to the quality control and new product development.

Specifically, in textile industry, ore and more manufacturers have noticed the importance to hear from customers and have turned their attention to the sensory study of their products. A typical marketing-oriented sensory study, which can be summarized as 'from products to perception, and then back to products', is illustrated in Figure 1-8. There are three major steps in this flow chart, which is explained as follows.

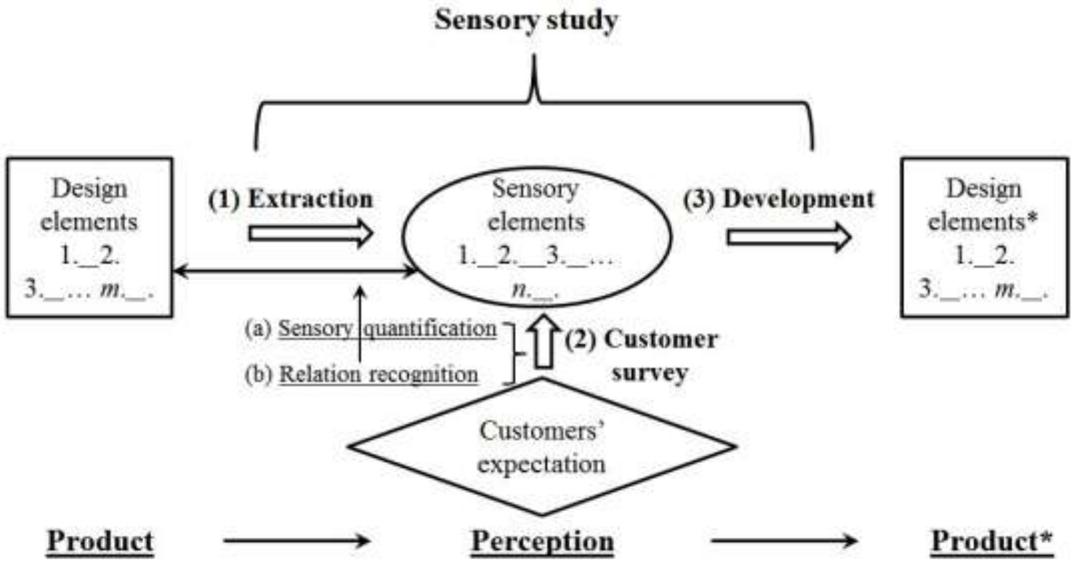


Figure 1 - 8 Flow chart of a marketing-oriented sensory study (*signifies 'after modification')

(i) Extraction. This is the first step of the sensory research, in which the textile products are analyzed using sensory techniques (which would be explained in detail later) into a set of sensory elements. Taking the haptic evaluation as an example, the elements can be the tactile properties such as 'roughness', 'stiffness', 'thickness' and so on, which are decided by the specific end-use of the fabric.

(ii) Customer study. This is a critical step throughout the study which consists of two major works, i.e. the quantification of customers' sensory preference, and the recognition of the relations between sensory and design elements of the product, respectively. Firstly, a sensory survey is carried out on customers according to the sensory space built from the previous step. From this step, customers' expectations about the specific textile product are measured and analyzed. For example, for a summer blouse, after investigation, it is found that the tactile properties 'soft', 'thin' and 'cool to touch' are preferable during daily wear. And then, on this basis, the relations between the sensory elements and the design elements (e.g. the weave, yarn density, yarn thickness and so on) of the textile product are studied using techniques for pattern recognition being either classical statistical methods (PCA, linear regressions, etc.)

[ANDERSON, 1998] or intelligent tools (fuzzy inference, artificial neural networks, etc.)[RUSSELL, 2003], which paves the way for the next step of the research.

(iii) Development. Here comes the final step of the study where the quantified sensory preference of customers is fused into the new design of the product according to the modeled relations between the two. So far, a customer-oriented product is developed.

With respect to haptic study of textile products, the above procedure is specified as, (i), the tactile properties are extracted as sensory elements in the first step; (ii), the tactile preference is obtained by conducting customer evaluations, on the basis of which the relations between fabrics' tactile properties and the product elements are modeled; (iii), new textile products fused with customers' tactile preference is developed. For other categories of sensory study, e.g. visual research, similar procedures are followed. The difference is that the product elements are the appearance features of the apparel item, such as the style, color and detail decorations, etc.

1.2.1 Basic notions about sensory analysis

In this part, we are going to present some basic notions about sensory analysis. These notions include the sensory panels, experimental design, and modeling of relations between different sensory data.

1.2.1.1 Sensory panels

Sensory evaluation is carried out by one or several sensory panels. A panel is a group of individuals organized to evaluate a set of representative samples. During a sensory evaluation, each individual or panelist is asked to, according to their professional experience, give a score (being numeric or linguistic) to a set of linguistic descriptors selected for the samples to be evaluated.

According to Dijksterhuis [1997], the sensory panels can be generally classified into the following five categories:

(1) Panels of experts: the experts specialized in using specific techniques to evaluate typical products and define evaluation criteria.

(2) Panels specialized in analysis of quantitative description: the panelists trained to evaluate the products using standard linguistic terms.
(3) Panels of free choice: the panelists trained to evaluate the products using their own words.
(4) Panels of consumers: the naive (non-trained) consumers invited to evaluate the products in a laboratory whose experimental condition is under control.
(5) Panels from streets: the naive (non-trained) consumers randomly recruited from, for example, commercial centers, to answer the pre-designed questionnaires.

From the street panels up to expert panels, the training level and the involvement of specialized knowledge gradually increase while the influence from personal hedonic preference decreases, which is shown in Figure 1-9.

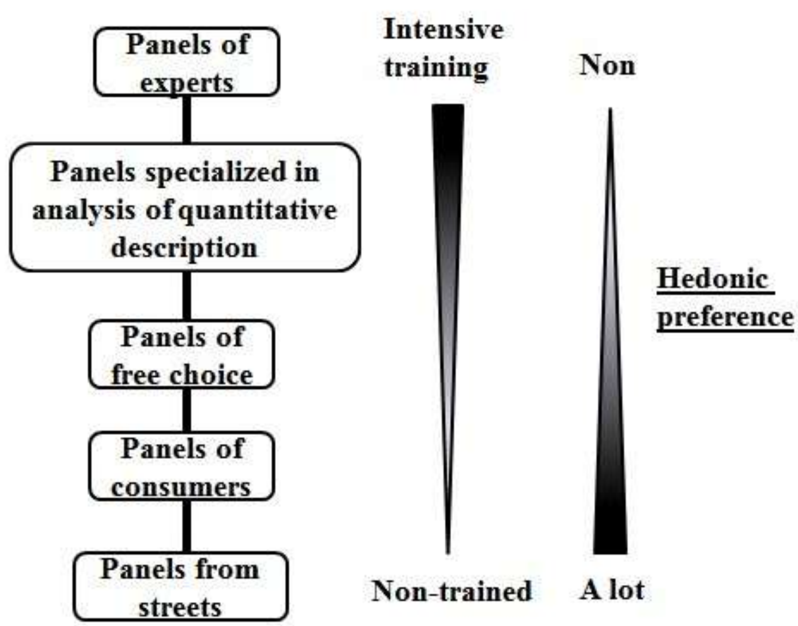


Figure 1 - 9 Level of training intensity and hedonic influence for each kind of panel

1.2.1.2 Design of experiments

Standardized design of experiments is the premise of obtaining reliable data. As the data structure for different types of panels is different, the corresponding design, including the detailed experimental procedures and the recruitment of the panelists, should be different too. If the sensory panel consists of non-trained consumers, an appropriate questionnaire should be designed to trigger the responders' true and exact perceptions about the specific samples to be evaluated.

On the other hand, if the sensory panel is composed of specialized experts, the evaluation procedure should be carefully designed to help the panelists acquire the maximum amount of information from the samples to be evaluated. A practical problem during the collection of sensory data is to design an optimal experimental plan according to which the products of interest can be evaluated in the same way with a minimum number of tests under the situation that the number of products is big and the time for evaluation is limited.

During the generation of a design of experiments for sensory analysis, we should keep in mind the research strategy, involving the objectives of the tests, the way of posing problems and the method of exploiting the obtained results. They will influence all the sectors involved in a sensory experiment, including the preparation of samples, the way of displaying the samples, the definition of evaluating scales and techniques, and the arrangement of experimental procedures, etc. Most of the existing work about design of experiments is presented in the context of physical measurement [Cochran, 1957], [PUKELSHEIM, 1993], [Peace, 1993]. When they are applied to deal with sensory analysis, some special needs should be considered. According to the work of [Stone, 2003], these special needs come from the significant difference between instrumental measurement and sensory evaluation that the responses of the assessors or panelists are easily influenced by their knowledge about the samples of interest and their experience in precedent experiments. In this case, some proper methods like the so-called balanced-blocked designs should be used to prevent the cross interaction between the panelists and the sample representations, and ensure all the experimental samples are evaluated in the same way for each panelist.

1.2.1.3 Modeling of relations in sensory analysis

(1) Multisensory analysis

From the illustration in Section 1.2.1, it is known that the most significant part of a sensory study is the communication between product elements and human elements. For an apparel item, the product elements consist of two categories; one is the elements about products' aesthetic design, such as styles, colors, etc., the other is the elements about products' qualities, including the fabric physical parameters (weave, yarn density, yarn twist, etc.), the tailoring and sewing parameters, etc. And the human elements refer to either the experts' professional knowledge or consumers' personal preference which are expressed through sensory surveys. To exploit the relations between the product elements and human elements about a specific product will make it possible for the manufacturers to sensitively detect the changes of market, and integrate consumers' demand into new product designs.

Actually, the above mentioned relation is one of the two principal relations to be concerned in sensory analysis. The other type of relation is the so-called multisensory relations referring to the relations between different human perceptions about a specific product which develops the so-called multisensory analysis. Further, the multisensory analysis comprises mainly two kinds of study. One is aimed to formalize and characterize consumers' complex emotional and social demands on the products which give rise to the concepts such as the comfort, well-being, health care, sustainable development, etc. For the other kind of multisensory analysis, researchers are dedicated to study the interactive relations between different human perceptions so as to enrich to the biggest extent our consumers' purchasing experience and increase their general satisfaction towards the specific product. For example, nowadays, a lot of work has been dedicated to the cooperative and compensatory study of multisensory information. The researchers are seeking the possibility of compensating or improving people's one perception by manipulating other perceptions. This branch of work is especially important for the online transaction or e-shopping during which only visual or auditory information about the products is available for the consumers. In order to provide the consumers with the most possibly complete and real sense of the product, for example, to obtain fabric tactile information in a non-haptic environment, it will be significant to fill this sensory gap left by the deprivation of haptic experience, by making the best use of the available visual or auditory information.

(2) Modeling of relations between different sensory datasets

No matter which type of relation is concerned, it is important to find an appropriate mathematical approach to model the relations between different datasets.

Many data mining methods have been developed for exploiting complex relations among multiple datasets. Nowadays, the most commonly used methods are based on statistics, including Linear regression analysis [WEISGERG, 2005], Principal component analysis (PCA) [JOLLIFFE, 2002], Multidimensional scaling [HOLLINS, 1997], [PICARD, 2003], Multiple factor analysis [HOWORT, 1958], [LE DIEN, 2003] and various kinds of correlation coefficient analysis [WOLFGANG, 2007]. These methods are efficient in solving many problems in sensory evaluation due to their good capacity of studying linear patterns of different information and then discovering correlations therein from a big base of numerical data. And also for this reason, they have been widely employed to various research fields in social science, such as economics, medicine, biology and others. [AGREST, 1997]

However, since modeling of relations between different sensory datasets constantly encounters problems dealing with uncertainty and imprecision, the classical methodologies are gradually showing their drawbacks in practice. First, when a problem is dealing with human knowledge, the concerned relations are often nonlinear. The application of the frequently used statistical techniques might cause important information loss due to their linearly structured models. Second, in many cases, there exists high uncertainty and imprecision in sensory analysis due to non-unified linguistic evaluation scores. But most of the classical analysis methods can only process perfect and complete numerical data without any uncertainty and imprecision. Third, the classical methods cannot always lead to precise and significant physical interpretation of data, and the obtained correlation results cannot be used to analyze all types of relations between datasets such as inclusion, causal and association relations. Finally, the classical methods often have strict requests on the size and distribution of the database. But collection of a great number of sensory data is not as quick and direct as mechanical measurements. It is quite time-consuming and sometimes unpractical for many researches, for example in pilot studies. With a limited collection of samples, it is unlikely to obtain good fit modeling results using the classical methods.

In this situation, intelligent computational techniques, such as ANN (Artificial neural network) [FAUSETT, 1994], GA (Genetic algorithm) [GOLDBERG, 1989], fuzzy logic [ZADEH, 1965], [SUGENO, 1993] and many hybrid applications of these tools [RUAN, 1997], have largely been applied to modeling and analysis with sensory data. They have high capacity in, (i) solving nonlinear problems, (ii) dealing with both numerical and linguistic data, (iii) modeling human expert reasoning so as to produce precise and straightforward interpretation of results, and (iv) computing with relatively small sets of data and without need of any preliminary or additional information like probabilistic distributions in statistics. Compared with the classical methods, the intelligent techniques have been practiced in many fields of sensory analysis such as food, automobile, cosmetic and textile, and gained more successful and significant results ([ZENG, 2008], [ZENG, 2004], [XUE, 2009], [XUE, 2011], [XUE, 2012].

1.3 Proposed methodology

Nowadays, as Internet has become the most used information resource in the world, the way of consumption is changing considerably. E-shopping has emerged and is becoming a generally accepted purchasing mode due to its economical and convenient features. With an ever larger market being accessible to manufacturers and retailers, e-commerce is steadily growing, which makes the interaction between consumers and business expand and flourish to an unforeseen height.

In practice, as one of the most life-related goods, apparel products enjoy an indispensable large share in the overall online transaction. According to Internet Retailer, 34% of British consumers shopped online clothes in 2010, up from 25% in 2009. Besides, the U.K.'s online apparel sales were estimated to grow 60% by 2015 [Internet retailer, 2011].

Although e-shopping is becoming popular, there still exists consumers' strong need to fully "feel" textile items before making a final purchasing decision. One big barrier making the current online apparel shopping still far from satisfactory is the products' intangibility during the transaction. The virtual fitting room is a recent approach to resolve consumers' demand to make choices from various clothes styles and then examine the physical fitness of the preferred items to their own body shapes (PROTOPSALTOU, 2002). In spite that the fitting system can stimulate with some success people's try-on behavior as it is in a real store, fabric tactile properties of clothes still remain as a mist in this virtualized environment.

Since 'Fabric hand' was defined by the Textile Institute in 1975 as 'the subjective assessment of a textile material obtained from the sense of touch' [ALI, 1994] and Fritz once stated in his work that "people are capable of making objective, quantitative, and repeatable assessments of their sensations" [FRITZ, 1990], we have reasons to believe that the most effective way to study fabric tactile properties (or fabric hand) should be from the perspective of human's natural perception. For a long time, fabric hand is studied on the basis of real touch experiments, during which the evaluators are introduced to directly handle the textile fabrics and give assessments according standardized techniques and criteria [PHILLIPE, 2004]; [XUE, 2009].

But, online shopping happens in a non-haptic environment. In this case, vision becomes maybe the only accessible and barrier-free source of perceptual information for the consumers. Besides, according to physiological psychology, over 80% of our daily information to be processed by the brain is perceived through our eyes [WANG, 2001]. On this premise, we are considering the possibility to study fabric tactile properties from visual information.

To date, when we talk about the visual studies of textile products, most work are found in the aesthetic and behavioral researches on the color and structural appearance of textile products [JOHNSON, 1979]; [SODA, 2008]; [WANG, 2006]. For example, Kawabata, Niwa et al. developed a model to predict the quality of the appearance of men's suit from fabrics' mechanical properties [KAWABATA, 2002]. However, few studies have tried to explore fabrics' tactile properties from perceived visual information [KOHKO, 1995].

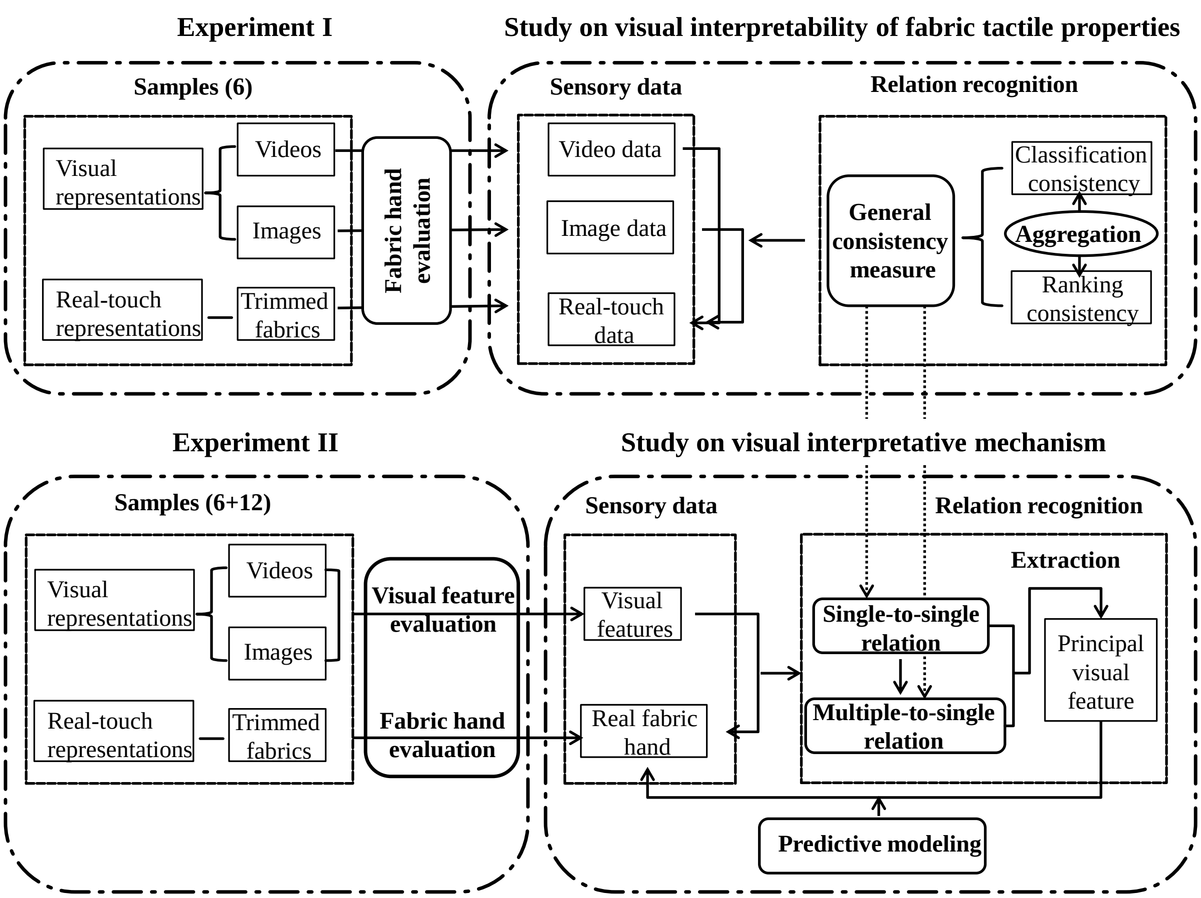


Figure 1 - 10 General scheme of our study

In the current thesis, we propose for the first time a systematic way of studying the feasibility, and further, the mechanism of visual interpretation of fabric tactile properties. Figure 1-10 shows the general schema of our study. As is shown in this figure, the entire research is composed of two major objectives which are realized in two consequent sensory experiments. The first objective which is realized in Experiment I is to study the extent to which fabric tactile properties could be interpreted through samples' visual representations (i.e. videos and images); while the second objective corresponding to Experiment II is, on the basis of the first experiment, to investigate the visual interpretative mechanism.

In the following, according to the two research objectives, we shall give a general description of the experimental methods and the data analysis approaches to be used in the study.

(1) First objective: Study on visual interpretability of fabric tactile properties

(i) <u>Experiment I:</u>

In this experiment, six textile fabrics with typical tactile properties were selected and made into flared skirts as the experimental samples. Visual (video clips and static photos) and real-touch representations were prepared for each sample. Fabric hand evaluations were carried out by a group of panelists in the corresponding three experimental scenarios, video, image and real-touch scenarios, respectively.

One commonly used method in sensory science is the so-called descriptive analysis [STONE, 2003], or profiling analysis, which was initially developed in food industries to measure sensory differences among a set of products through quantification of well-defined attributes [LAWLESS, 1999]. Nowadays, its application has been found in many fabric hand studies. [BISHOP, 1996]; [PHILIPPE, 2004]; [XUE,2009]; [ZENG, 2003]; [ZENG, 2004]; [XUE, 2011]; [XUE, 2012]

In the current study, we follow the principles of descriptive analysis to obtain data from different sensory modalities (i.e. visual and real-touch) during tactile perception of textile products. Reliable sensory data are acquired through the standardized design and implementation of experimental plan which includes the generation of fabric tactile descriptors, determination of evaluation scales and techniques, preparation of evaluation questionnaires, training of panelists, and design of experimental procedures.

(ii) <u>Relation recognition:</u>

The evaluation results obtained from different experimental scenarios were formalized as the sensory data to be utilized for further processing. In the current study, we have proposed a novel approach to investigate how much tactile information of textile products can be transmitted to assessors through different visual displays.

This approach deals with the ideas of both fuzzy sets [DUBOIS, 1996] and rough sets theories [PAWLAK, 1982]. Above all, the so-called inclusion degree from rough sets theory was applied as a basis to discover the classification consistency, which is the core aspect of the whole method, between the perceived tactile information about the samples obtained from different sensory modalities (i.e., the touch and the vision). In order to make this measure better adapt to the current sensory problem which is characterized by a lot of uncertainty and imprecision, a fuzzy set approach was applied to modify it by quantifying the vagueness of sensory observations. Then, as another important aspect of the approach, the ordinal correlation between different sensory data was measured using a non-parametric method called Kendall's correlation coefficient. Finally, in order to create a reasonable integration of the previous two indices, a general consistency measure was constituted by introducing the expert knowledge into a fuzzy inference system.

The proposed approach is capable of detecting nonlinear patterns lying beneath sensory data while being safe to use a comparatively small number of experimental samples. Moreover, it is believed to be able to prevent the "black box" phenomenon encountered in many modeling techniques [LIPPMANN, 1987], and produce robust and interpretable results.

(2) Second objective: Study on the visual interpretative mechanism

(i) <u>Experiment II:</u>

On the basis of the observations obtained from Experiment I, in this consequent experiment (Experiment II), twelve more samples were added to constitute a sample base of eighteen flared skirts in total (plus the previous six samples). The process of sample preparation is the same as in Experiment I that each fabric corresponds to three sample representations, video, image and real-touch, respectively.

Two kinds of sensory evaluations were carried out in this experimental session.

a) Visual feature evaluation

A group of panelists were recruited to evaluate the visual features of the samples skirts through their visual representations. What's different from Experiment I is that, in this session, the visual representation for each sample was the combination of both video and image displays. That is to say, the evaluation was based on all the possible visual information about the sample including both its static and dynamic displays.

Similar procedures were followed in this session to generate visual characteristic descriptors, determine evaluation scales and techniques, prepare evaluation questionnaires, train panelists and so on. The visual feature evaluations were implemented by the panelists according to standardized experimental procedures.

b) Fabric tactile evaluation

A group of panelists were invited to evaluate the fabric tactile properties of the eighteen samples in the real-touch condition. The evaluations were carried out in the same way as in Experiment I that the same tactile descriptors, evaluation scales and techniques were used, and similar experimental procedures were followed. What's a bit different is that due to the relatively big amount of samples present in this session, some measures have been taken to simplify the experimental procedures so as to obtain reliable responses from the panelists. For example, the display order of the samples was optimized.

(ii) <u>Relation recognition:</u>

Two steps were taken to investigate the visual interpretative mechanism of fabric tactile properties. The first step is to find for each tactile property the visual features that have the most significant impact. From the computational point of view, this step is in fact the process of feature selection which is aimed to reduce the complexity of the system. Being different from mechanical measurements, there exists frequent and widespread sensory interaction during human perceptions. So, the relations to be concerned in this study involves two aspects, one is the single-to-single relations between one tactile property and any visual feature; the other is the multiple-to-single relations between one tactile property and several principal visual features, which resembles the basic structure of the visual interpretative mechanism.

a) Single-to-single relation

The same consistency measure as the one used in Experiment I was applied to recognize the single-to-single relations between each tactile property and all the visual features. In this step, relevant visual features were selected to claim big impact on each tactile property according to their higher consistency values, while those visual features with lower consistency degrees were screened out of further consideration.

b) Multiple-to-single relation

On the above basis, the second step is to quantify the multiple-to-single relations, which finally unveils the visual interpretative mechanism for each tactile property. In this step, the previous consistency measure was modified to adapt to the need of communicating one tactile property with more than two visual features. After applying the modified consistency measure, for each tactile property, several principal visual features were extracted.

c) Predictive modeling

Finally, a predictive model between each tactile property (as output data) and its principal visual features (as input data) was developed based on an Adaptive Network-based Fuzzy Inference System (ANFIS). So far, the interpretative mechanism of visual representations to fabric tactile properties has been discovered.

1.4 Conclusion

In this chapter, we have presented the background knowledge about our study. Firstly, we introduced some basic notions about human perceptions and their relations with the evaluation of textile products. Then, we have described the definition, principles and recent development of sensory analysis with its application to textile products. Finally, the general schema of our research was put forward along with a brief illustration of the used sensory methods and mathematical approaches.

CHAPTER 2: Hypothetical discussions on multisensory perception of fabric tactile properties

The aim of our thesis is to investigate the possibility, and then on this basis, the mechanism of interpreting fabrics' tactile properties through samples' visual representations. In this chapter, we are going to introduce in depth the two concerned human senses (i.e., touch and vision) and their cooperation during multisensory perception of fabric tactile properties from the perspectives of physiological psychology and cognitive psychology. The discussion carried out in this part will provide ground for the hypothesis which is of great significance throughout the thesis, that fabrics' tactile properties could be, to a large extent, perceived in a non-haptic environment, and to be specific, by people's eyes.

2.1 Fabric tactile properties and haptic perception

In this part, we are going to introduce some basic notions about the haptic perception of textile products, including the definition of fabric tactile properties and the physiological basis of human haptic system.

2.1.1 Fabric tactile properties

The 'sense of touch' is a complicated concept. It in fact comprises two senses—the cutaneous sense and kinesthesis. [BORING, 1942]; [BROWN, 1979]; [GORDON, 1978] Viewed functionally, the cutaneous sense provides awareness of stimulation of the outer surface of the body by means of receptors within the skin and the associated nervous system (just like the current study, to date, most studies have focused on sensory receptors located within the hairless skin of the human hand [JONES, 2006], whereas the kinesthetic sense provides the observer with an awareness of static and dynamic posture on the basis of the information originating within the muscles, joints, and skin during touching. In fact, the cutaneous stimulation serves only to indicate contact with the stimulus, while variations in kinesthetic stimulation convey all of the spatial information essential to performance of the task. [LOOMIS, 1986]

Generally, the assessment of touch of a textile product is generated by active exploration of our hands in which both the skin touch stimulation and the instant feedbacks of the fabric against our exploration motions is considered. [LEDERMAN, 1987] Thus, physiologically, both the cutaneous and kinesthetic sensations are included during touch evaluation. Actually, the term 'tactile' is referred to only the cutaneous sensation of an object according to psychology. But in practice, many researches about fabric hand have loosened the use of this term. [PICARD, 2003]; [FERNANDES, 2008]; [HOLLINS, 2000] 'Tactile' is referred inclusively to all perception mediated by cutaneous sensibility and/or kinesthesis. In this situation, our study continues to use this terminology.

Here, we give the definition of *fabric tactile property* or called *fabric hand,* which was proposed by the *Textile Institute* in 1975, as 'Subjective assessment of a textile material obtained from the sense of touch'.[ALI, 1994] Being different from the previously mentioned notion of natural contact between human body and the apparel items (see Section 1.1.2.1), the touch we refer to here and in the whole study is the process of acquiring the tactile properties of a textile product by manually manipulating the fabric in an experimental context.

The word 'haptic' originated from the Greek word 'haptikos' which means 'to touch'. It should be clear that haptic perception of objects' properties is tightly bound to the nature of contact [WIKIPEDIA, 2012(a)]. For textile products, according to the type of tactile properties to be explored, the haptic procedures (see two examples in Figure 2-1) can be holding the fabric in the hand to assess its weight; placing statically or moving back and forth the fingers or palms on the fabric to feel its surface temperature (warmness) or textures such as roughness, fuzziness and slipperiness; or pressing, stretching and grasping the fabric to sense the thickness, hardness, elasticity and flexibility, respectively; so on and so forth.

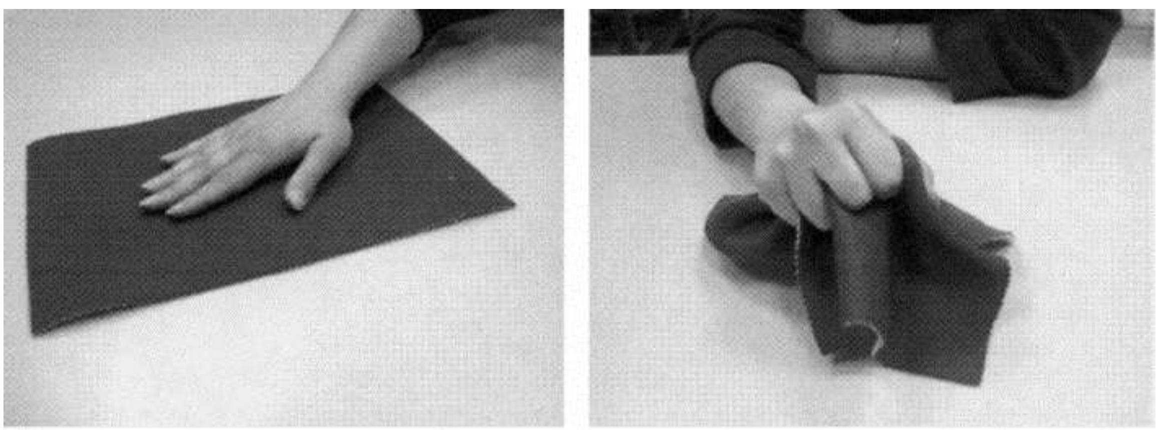


Figure 2 - 1 Some gestures of haptic exploration of fabric tactile properties (from left to right, static contact and grasping, respectively)

From the foregoing, the haptic system uses sensory information derived from cutaneous stimulations together with kinesthetic stimulations. On this basis, a brief introduction about the physiological mechanism of haptic perception is presented in the following.

2.1.2.1 Haptic receptors

As was introduced previously, the cutaneous sensation deals with the outer stimulations having contact with our skin and has awareness of the texture, compliance and temperature of the stimulus. Cutaneous receptors are found across the body surface. There are three types of cutaneous receptors responding to various stimulations on the outer surface of the body. [BIRDER, 1994] They are, respectively, mechanoreceptors detecting pressure, force and vibration, thermoreceptors responding to temperature changes, and nociceptors which transduce harmful stimuli that we perceive as pain (induced by, for example, intense heat and chemicals). Under the context of our study, only light hand touch is concerned to simulate the daily wearing of the textile products, thus, the nociceptors are not to be dealt with in the following discussion.

Figure 2-2 shows the cross sectional view of skin where various types of sensory receptors are embedded. There are about six types of receptors whose corresponding functions are listed below.

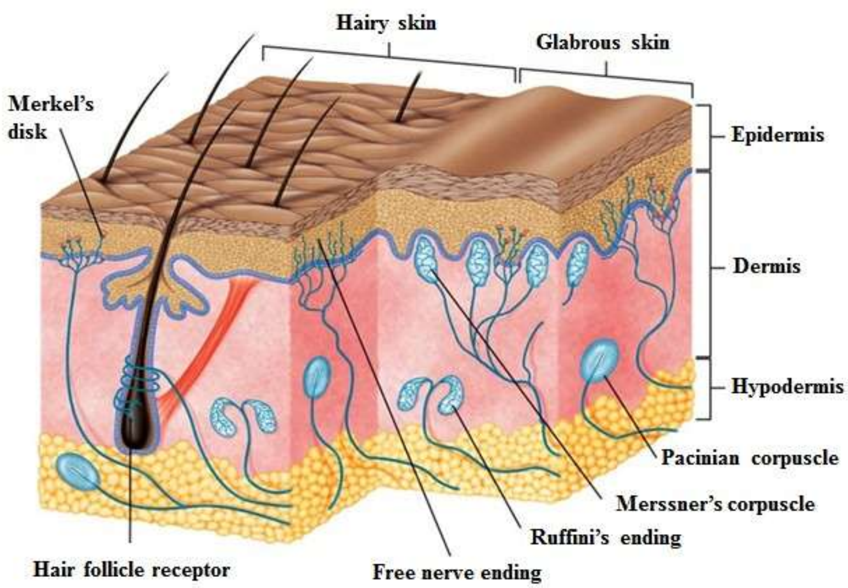


Figure 2 - 2 Cross sectional view of skin with sensory receptors embedded in

(1) Free-nerve ending: situated between epidermal cells. It is sensitive to light touch, temperature, etc.
(2) Pacinian corpuscle: also called lamellated corpuscle, located in deep layer of the skin, is sensitive to vibration and deep pressure and involved in the fine discrimination of texture.
(3) Meissner's corpuscle: most common reception in glabrous (hairless) skin such as fingertips. It is responsible for perceiving sensations of fine touch, pressure, and low-frequency vibration.
(4) Ruffini's ending: located in the reticular (deep) dermis. It is sensitive to pressure and distortion of the skin.
(5) Mercel's disks: located in the superficial layer of the skin. They are discriminative touch and light pressure receptors.

(6) Hair follicle receptor: situated around hair root. It is good at detecting initial contact and subsequent movements.

On the other hand, with respect to the kinesthetic senses, the corresponding sensory receptors are called proprioceptors which are only responsive to stimuli coming from inside our body (physiologically, the word 'proprioception' is referred to the ability to sense the position, location, orientation and movement of the body and its neighboring part [WIKIPEDIA, 2012(b)]. There are two major types of proprioceptors, namely, the muscle spindle (or stretch receptors) and the Golgi tendon organ. The muscle spindles are distributed within the fleshy belly of each skeletal muscle and are responsible for monitoring the degree of stretch of the muscle. And the so-called Golgi tendon organ is located with the tendon near its attachment to the muscle fibers and detects relative muscle tension.

Fabrics tactile properties as stimulations to these receptors are transduced into action potentials and ready for a travel through specific sensory pathways to the somatosensory cortex in the brain.

2.1.2.2 Sensory pathways of haptic perception

When we talk about the perceptual pathway of 'haptics', we are in fact referring to the so-called somatosensory system [RUSTIONI, 1989]. It is a diverse system comprising the receptors and processing centers to produce cutaneous and kinesthetic senses.

For textile products, the haptic percepts include the surface texture, compressive resistance, tension to stretch, the touching temperature, etc. Viewed physiologically, different stimulation will trigger different perceptual mechanism. In other words, the sensory inputs processed by the somatosensory system travel along distinct nervous pathways, depending on the information carried, to finally reach the primary somatosensory cortex which is located in the lateral postcentral gyrus of the parietal lobe. There are two major pathways which are believed to be responsible for haptic perception of textile products. One is the posterior (dorsal) column-medial lemniscal (DCML) pathway which carries discriminative touch (referring to fabric texture recognition) and proprioceptive information (corresponding to kinesthetic senses) from the body. The other is the spinothalamic pathway which carries crude touch (contrasting 'discriminative touch', is a sensory modality which allows us to sense that something has touched us, but without being able to localize where they were touched. In this sense, crude touch is not where we focus in the current study), pain and temperature information from the body. Since the DCML pathway deals with most of the haptic stimulation concerned in a fabric hand evaluation, it is considered as the major somatosensory pathway in our context which deserves more detailed introduction.

(1) Dorsal column-medial lemniscal pathway (DCML)

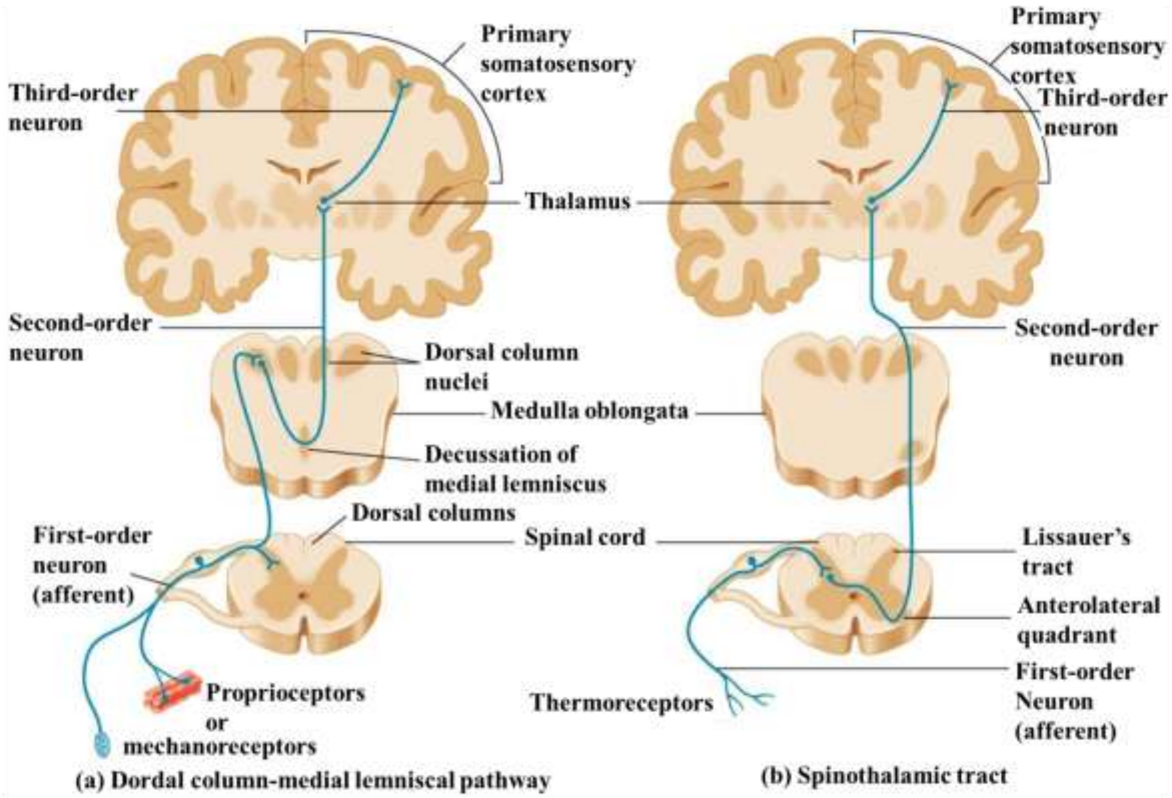


Figure 2 - 3 Illustration for DCML and ST pathways

Figure 2-3 (a) shows a brief illustration of the DCML pathway for processing discriminative touch and proprioceptive senses. In fact, any sensory pathway consists of a chain of neurons, from receptor organ to cerebral cortex, that are responsible for the perception of sensations. For somatosensory system, specifically, between the point of stimulus reception and the postcentral gyrus, there is a minimum of three neurons in series. The following illustrates the DCML pathway from the perceptive of these three neurons.

(i) The pathway transmits information from mechanoreceptors and proprioceptors. First order neurons (afferents) which are located in the periphery enter the spinal cord through the dorsal root. The main axons ascend the spinal cord in the ipsilateral (def: on or relating to the same side of the body) dorsal column and end in the dorsal column nuclei in the medulla oblongata where they synapse with second-order neurons (afferents).

(ii) The second-order neurons (afferents) which are regarded as the interneurons of the sensory pathway cross over to the contralateral side of the medulla in the medial lemniscus and ascend to the forebrainstem, where they reach a mass of gray matter called the thalamus. In the thalamus, the interneurons synapse with the cell body of the third neuron.

(iii) Finally, the axon of the third neurons (afferents) in the thalamus projects up through the cerebral hemisphere to the somatosensory cortex located in the postcentral gyrus.

(2) Spinothalamic tract (ST)

Figure 2-3 (b) depicts the pathway (ST) responsible for processing temperature stimulations. The illustration is also based on the three essential neurons.

(i) The pathway transmits information from thermoreceptors. The first-order neurons from the periphery enter the spinal cord through the dorsal root and may ascend or descend (a few spinal segments) along Lissauer's tract before synapsing with second-order neurons in the dorsal horn.

(ii) The second-order neurons cross to the contralateral side of spinal cord and ascend in the anterolateral quadrant of the spinal cord through the brainstem to the thalamus.

(iii) The third-order neurons in the thalamus ascend to the somatosensory cortex.

Ever since the haptic stimulations are understood as neural signals by our brain, the sensation process is completed. But from the perspective of perception, to be sensed is still not enough. The association area located in the surrounding of the primary somatosensory cortex plays its important role in integrating translated haptic information with memories or emotions so as to obtain a rich experience about the perceived stimulation. For example, when we touch the surface of silk, the sense of 'smooth' is the sense recognized by the primary somatosensory cortex through the above illustrated pathways, while the emotion of 'agreeable' during touch is the result of integrating the touch of smooth with our previous haptic preference.

2.2 Visual perception of fabric tactile properties

2.2.1 Physiology of visual perception

From the foregoing, we know that due to the vast perceptive field (or visual field) and the sharply responsive mechanism of our eyes, vision plays a very important role in the perception of either the aesthetic or comfort aspects of textile products. However, no matter the outside world will produce what a colorful image in our brain through the visual perceptive system, being, for the textile products, either the coloring, styling or textures, they, at the beginning, are just some lights different in intensity reflected from the objective stimuli. So, from the physiological point of view, they have the same sensory pathway which is to be briefly introduced in the following.

2.2.1.1 Phototransduction

Light rays enter the eye through a curved, transparent structure called the cornea, then pass through the pupil, an opening in the eyeball. The iris regulates the size of the pupil. Next, the lens focuses the light on the retina, a light-sensitive membrane in the back of the eye. The retina contains two types of photoreceptive cells, rod cells and cone cells, which detect the photons of light and respond by producing neural impulses (it is known that the cone cells which are concentrated in the central portion of the retina are responsible for detecting color stimulation, while the rod cells which are located at the edge of the retina permit vision in dim light). This phenomenon of conversion of light energy into neural impulses is known as 'phototransduction'. Figure 2-4 is an illustration of the eye anatomy. [CORNSWEET, 1970]; [DE VALOIS, 1965]

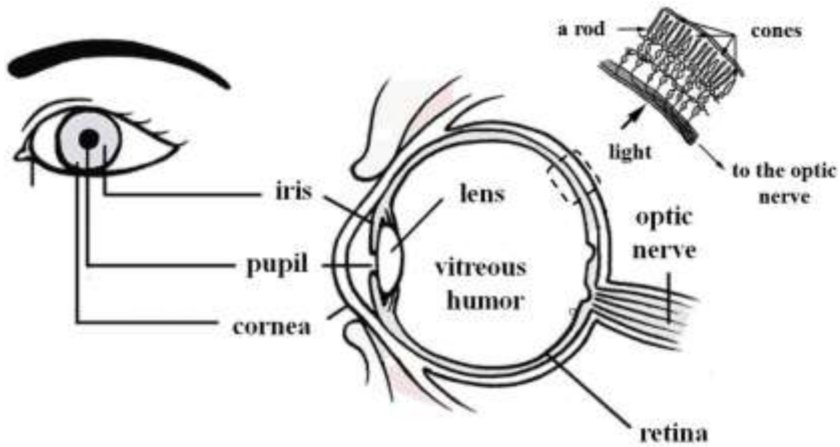


Figure 2 - 4 Eye anatomy

2.2.1.2 Sensory pathway

Figure 2-5 is a brief illustration of the neural pathway of visual perception from the retina upstream to the visual area of our brain. [BRINDLY, 1970]; [WANDELL, 1995] The neural impulses generated in the photoreceptors are transmitted by 'electrotonic conduction' to other cells of the retina, e.g. the ganglion cells. The axons of retinal ganglion cells exit the retina via the optic nerves. The optic nerves exit the eye in a region called the optic disc. It is a blind spot where no receptors are found in this region. The optic nerves cross at the optic chiasm, past which the axons of the retinal ganglion cells are known collectively as the optic tract.

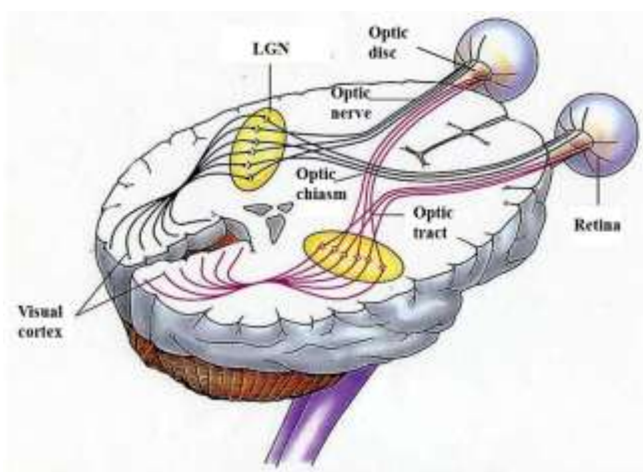


Figure 2 - 5 Visual pathway

The vast majority of axons of the optic tract terminate in the lateral geniculate nucleus (LGN), which is the visual part of the thalamus and serves as the primary relay nucleus for visual processing by the cerebral cortex. The right LGN receives information from the left visual field, while the left LGN receives information from the right visual field.

Most of the axons from LGN travel through the optic radiations and terminate in the visual areas in the occipital cortex at the back of the brain. The primary visual cortex (V1 or striate cortex) transmits perceived visual information through two primary pathways, called the dorsal stream and the ventral stream, to the surrounding areas of the cerebral cortex (association areas, or 'extrastriate' as contrast to 'striate') that are involved in complex visual perceptions. The dorsal stream, which includes the middle temporal area, leads from the striate cortex into the parietal lobe. This system is thought to be responsible for spatial aspects of vision, such as the analysis of motion, and positional relationships between objects in the visual scene. Apparently, the evaluation based on dynamic display of textile products depends on this mechanism. On the other hand, the ventral stream, which leads from the primary (or striate) cortex into the inferior part of the temporal lobe, is thought to be responsible for high-resolution from vision and object recognition. According to our study, the evaluation of fabric surface textures is related to this pathway. Figure 2-6 shows the V1 and extrastriate areas. [BRINDLY, 1970]

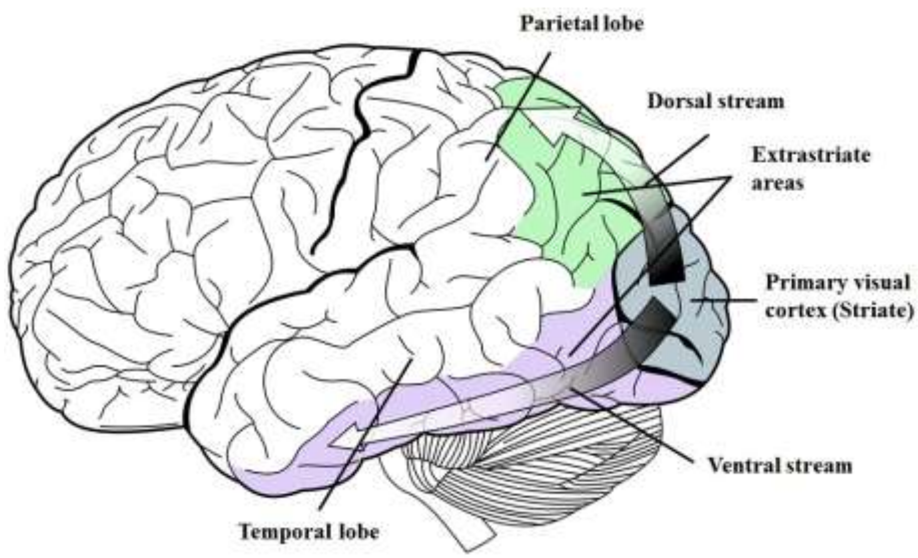


Figure 2 - 6 Primary visual cortex (V1) and association (extrastriate) areas

Similar to other senses, the extrastriate areas of visual cortex are also involved in associating the current visual experience with memories or emotions. In this way, for example, we are able to visually recognize the similarities of two skirts in photos, and make a hedonic choice between two men's suits according to our accumulated personal experience on the specific visual elements such as the shape of the collar, the coloring of the fabric, the design of the pockets, etc.

2.2.2 Fabric tactile perception via vision

As it sounds, the fabric tactile properties are predominantly thought of as a kind of properties that fall within the domain of touch. But according to our real-life experience, if we are deprived of the possibility to touch an object, we can still have access to a lot of information about it, including even the information which is naturally thought of as 'haptic-mediated'. For example, when we view a dress either behind the display window or in an online store, without the need to touch it, we have already got the information sufficient for making a purchase decision. The acquired information includes not only the visual aesthetic attributes (e.g., the coloring, styling, size and decoration designs, etc.), but also the tactile properties of the dress, such as the surface texture, touching comfort, thickness, approximate weight, and even the elasticity of the fabric.

But just as what we have discovered in the previous part, from the perspective of physiology, the type of stimulation that can be sensed and the sensory pathways are distinct for touch and vision. Then, what has made it possible for us to perceive haptic information through visual representations of textile products?

Concerning the visual interpretation of haptic information, there have been two major explanations that can be conceived. The first hypothesis is that the visual system is capable of directly judging fabric tactile properties (or some of them) almost as accurately as the haptic system. The second hypothesis is that fabric tactile properties are indeed haptic percepts, but in the visual condition the fabric is recognized and its tactile properties, as experienced haptically before in daily life, are retrieved from memory.

In fact, the above two hypothesis make senses to some extent while both of them are not completely correct. Since visual perception has high acuity and diverse perceptive field, the mechanism of visual interpretation of haptic information can be understood according to different tactile properties to be explored. It is believed that fabric surface properties (or textures) can be naturally perceived by visual observation, while other haptic properties tend to be perceived by retrieving memory about previous haptic experience.

2.2.2.1 Visual perception of fabric surface properties

To date, the most commonly assessed haptic property for an object (being no matter a textile fabric or any other object) is the physical features of the surface or called texture (i.e., for textile products, fabric surface properties). [BRODATZ, 1966] As was mentioned in the previous section, texture is multisensory, and is not restricted to the sense of touch. From the perspective of haptic exploration, the measures of texture tend to correspond to variations in magnitude along a single dimension (for a fabric, it is the dimension perpendicular to the surface). As used in the context of vision, texture refers to the variations of brightness (intensity of reflected light) of elements across a surface, which constitutes a 2D pattern. As Adelson and Bergen [ADELSON, 1991] put it, texture is 'stuff' in an image, rather than 'things'. Taking the roughness as an example, four cues are identified in visual perception: the proportion of image in shadow, the variability in luminance of pixels outside of shadow, the mean luminance of pixels outside of shadow, and the texture contrast.

A large body of work has been found in research on comparing the performance of haptic and visual (unimodal) perception of object textures. Most of the researches are carried out from the psychophysical point of view. In a very early study, Binns [1936] found no difference between the two modalities in the ordering of a small number of fabrics by softness and fineness. Björkman [1967] found that visual matching of sandpaper samples were small. Lederman and Abbott [1981] found that surface roughness was judged equivalently whether people perceived the surfaces by vision alone or haptic. Heller et al. [1982] designed a series of experiments to investigate the consistency of performance between the two modalities and found that vision and touch produced similar levels of accuracy in the perception of roughness. In another research concerning roughness discrimination of textiles, no difference between haptic and visual perception was found in an experiment with 10 subjects and four fabric samples [GUEST, 2003]. In an extensive comparison using natural surfaces, Bergmann Tiest and Kappers [2006] had subjects rank-order 96 samples of widely varying materials (wood, paper, ceramics, foams, etc.) according to their perceived roughness, using vision or haptics alone. Objective physical roughness measures were then used to benchmark perceptual ranking performance. Rank-order correlations of subjects' rankings with most physical measures were about equal under haptic and visual sorting.

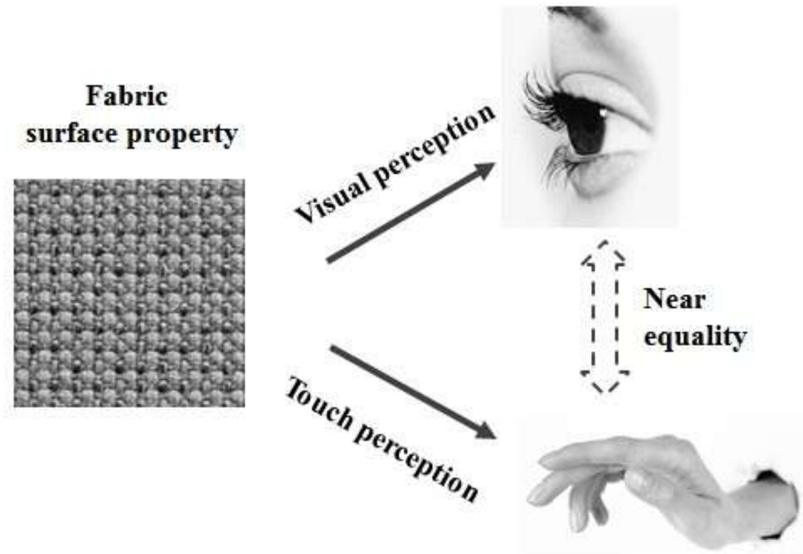


Figure 2 - 7 Visual and haptic perception of fabric tactile property

Therefore, a consensus has been reached that people find it natural to judge visual textures, and few systematic differences are found between texture judgments based on vision vs. touch (Figure 2-7). The neuropsychological mechanism that supports this conclusion has not been very clear yet. But some studies on the brain activations of texture perception via haptic and visual modalities still provide some useful clues. For example, it is found that although the pathways for encoding sensory information are independent for touch and vision, the principles of information processing, and neural resources are, to a large extent, shared across modalities. Besides, there are overlapped areas for visual and haptic perception of textures. A stilla and Sathian study [2008] shows that a right medial occipital area that is activated preferentially for haptic texture is tentatively localized in visual area V2. This area overlaps with a visual-texture responsive area corresponding primarily to V1. However, the lack of correlation between responses to visual and haptic textures in this area suggested that it houses regions that are responsive to one or the other modality, rather than containing neurons that can be driven by either vision or touch.

So, to summarize, firstly, both the haptic and visual systems have their own long-established pathways for perceiving objects' textures which are independent from each other. Secondly, objects' textures are easily obtainable by both the haptic and the visual senses. Although vision and touch have different emphasis during texture perception, i.e. vision appears to be biased toward encoding pattern descriptions while touch toward intensity variations, it is not the case that one sense dominates the other. This confirms the idea which has been mentioned several times in the above context that texture is not a concept restricted to any unimodal perception. Both touch and vision can transmit sufficient and reliable information concerning objects' textures and their perceived information well agrees with each other. So, with regards to our study, it is assumed that fabric surface properties (or fabric textures) can be well perceived by both haptic and visual modalities.

2.2.2.2 Visual perception of non-texture properties (associative memory)

From the foregoing, it is known that fabric surface properties can be well transmitted by visual textures varied in pattern features such as grain size, density or regularity, etc. In this sense, the visual perception of fabric surface properties can be considered as a direct and natural process with precision and efficiency. By comparison, for the other fabric tactile properties (e.g., bending, flexibility, stretchiness, and compressive softness, etc.) which fall into another group, namely, non-texture properties, there is no obvious or direct correspondence between fabric physical features and the visual elements (e.g. the coloring, silhouette, various static or dynamic effects of the corresponding textile product). The perception of these non-texture properties are considered to be dominated by the haptic system in contrast to the vision. However, our experience tells us that when touch is deprived we can still make estimations on fabrics' many non-texture properties via vision alone. For example, when a dress is put on a mannequin who is walking to and fro while making various postures, we can probably tell if the fabric is stiff or pliable, hard or soft without the need to touch it. The mechanism behind this phenomenon may be discovered from the perspective of cognitive psychology. [WIDROW, 2005]

Actually, in our daily life, we always perceive the outside world in a multi-channel mode. Our perception about an object is a rich experience comprising information obtained from various senses. For example, in an apparel store, when we evaluate the tactile properties of an apparel item, our haptic exploration is always accompanied by the visual observation. The crossmodal interaction of this kind exists extensively in our everyday perceptual behavior. According to neuropsychology, in a multisensory experience, the unisensory information is pooled together at some late stage in perceptual processing to produce a rich image about the object of interest. The supportive mechanism is called *associative memory* which is to be illustrated as follows.

Our perception of the external environment is in fact a process of gaining, storing and retrieving information. And indisputably, the ability that enables us to do so is memory. Accordingly, the three main processes involved in human memory are encoding, storage and recalling information. [ASCHOEKE, 2012]

Encoding is the crucial first step to creating a new memory. It allows the perceived object of interest to be converted into a construct that can be stored within the brain and then recalled by a prompt signal from a current set of information. Taking the bimodal (haptic and visual) perception of fabric non-texture properties as an example, the step of encoding is in fact the process of the specific stimulations (to be distinct between haptic and visual systems as was discussed in the previous sections), from being transduced by the haptic and the visual receptors to being recognized by the somatosensory and the visual cortex in the brain.

The perceived sensations about the fabric (haptic and visual) are then combined in the brain's hippocampus, an organ deep within the medial temporal lobe, into one single experience. Here, the hippocampus is responsible for analyzing the sensory inputs and ultimately deciding if they will be committed to long-term memory. It acts as a kind of sorting center where different sensations are compared and associated.

After the initial acquisition of sensory information, consolidation is the next process of stabilizing a memory trace. Before start, it is important to be clear about two facts. First, each neuron makes thousands of connections with other neurons, and memories and neural connections are mutually interconnected in extremely complex ways. Each memory is embedded in many connections, and each connection is involved in several memories. Thus, a single memory about an object may involve simultaneously activating several different groups of neurons in completely different parts of the brain. Second, neurologically, there is a process called 'potentiation' by which synchronous firing of neurons makes those neurons more inclined to fire together in the future. Therefore, as experiences accumulate, the above mentioned sensory associations are strengthened which is the so-called consolidation.

The consolidation is in fact the process of transferring short-term sensory memories into long-term memories. It should be noted that long-term memories are not stored in just one part of the brain, but are widely distributed throughout the cortex. In the above example, the haptic and the visual perceptions about the fabric are consolidated to become long-term memories which are stored in the distinct brain areas that initiated them, e.g. the somatosensory and visual cortices.

To make the retrieval mechanism better understood, we suppose that the sensory inputs concerning a single object are stored as vectors in a single 'file folder' or 'memory folder'. When the contents of the folder are retrieved, all the sensory information in this folder is obtained at the same time. For different objects, there are different folders. What's worth mentioning is that, the sensory signals are not fused, but they are simply recorded together in the same folder and retrieved together. This is a simplest cognitive memory system which is illustrated in Figure 2-8. When there comes a new sensory input, as a prompt, this set of inputs will trigger a sought of information association between the current inputs and the existing memory folders. Once an association is discovered, all the memories no matter they are from haptic, visual or auditory systems will be recalled. In the above example, since haptic and visual memories about a kind of fabric have been associated to constitute the so-called memory association through the accumulation of bisensory experiences, it is quite possible that in the absence of any sensory modality (for example, touch is deprived in the current case), the perception of the absent information can be achieved by the remaining sensory modality (in this case, the vision system) as long as the prompt inputs are meaningful (i.e., enough for triggering a retrieval of the memory associations containing related haptic information). This mechanism of memory association is very important in the so-called 'quasi-perception' which resembles the perceptual experience occurring in the absence of the appropriate external stimuli.

To summarize, it is confirmed that visual interpretation of fabric tactile properties is theoretically achievable. Therein, fabrics' surface properties (or textures), without being biased towards the haptic system, can be well perceived through visual representations. On the other hand, as regards to the non-texture properties, visual interpretation is possible, but the precision and efficiency are based on the intensity of memory association between the absent sensory modality and the existing which is determined by accumulated multisensory experience.

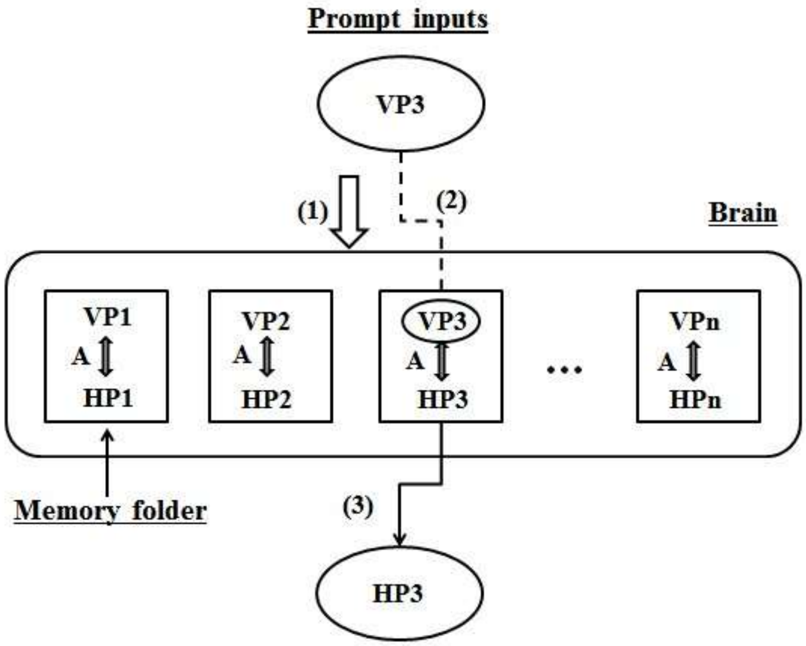


Figure 2 - 8 A simple cognitive memory system

(In this figure, VP and HP denote visual percept and haptic percept respectively; A is short for 'association'; (1), (2) and (3) represent the process of recalling HP3, therein, (1) triggering a retrieval from the prompt inputs (VP3); (2) matching prompt inputs with corresponding memory folder; (3) extracting absent percept (HP3) from recalled memory folder.)

2.3 Conclusion

In this chapter, at the beginning, we put forward the definition and some basic notions about fabric tactile properties. Since, according to our intuition and general knowledge, the perception of object tactile properties is bound to our haptic system, in the following context, we first presented the physiological basis of haptic perception. But, our daily life experience tells us that sometimes what we touch can be seen as well. So, then, we discussed the possibility of perceiving tactile properties through vision from the perspectives of visual physiology and cognitive psychology. Some hypotheses have been made that fabric surface properties (or texture properties) can be naturally and easily perceived by our eyes, while the non-texture properties such as bending, stretchiness, and so on can be visually perceived, but the precision is dependent on the intensity of the so-called memory association.

CHAPTER 3: Computational techniques

In our thesis, we have proposed a systematic approach based on the so-called 'fuzzy inclusion degree' to study the relations between visual and haptic perceptions of fabric tactile properties. This novel approach is developed from the ideas of rough sets and fuzzy sets theories which belong to the mathematical branch of approximate reasoning. In this chapter, we will present the theoretical basis of the computational techniques that are concerned in our approach.

3.1 Vagueness and Approximate reasoning

One of the fundamental tenets of modern science is that a phenomenon cannot be claimed to be well understood until it can be characterized in quantitative terms. Viewed in this perspective, much of what constitutes the core of scientific knowledge may be regarded as a reservoir of concepts and techniques which can be drawn upon to construct mathematical models of various types of systems and thereby yield quantitative information concerning their behavior. [WILLIAM, 1891]

Given our veneration for what is precise, rigorous and quantitative, and our disdain for what is fuzzy, unrigorous and qualitative, it is not surprising that the advent of digital computers has resulted in a rapid expansion in the use of quantitative methods throughout most fields of human knowledge. Unquestionably, precise computing has proved to be highly effective in dealing with *mechanistic systems* whose behavior is governed by the laws of mechanics, physics, chemistry and electromagnetism. But the same remark cannot be given to *humanistic systems*, by which we mean the systems whose behavior is strongly influenced by human judgment, perception or emotions. [NEWELL, 1972] It may well be the case that the conventional techniques of system analysis and computer simulation, which are based on precise manipulation of numerical data, are incapable of dealing with vague (imprecise) concepts involved in humanistic systems.

Indeed, in our real world, humanistic problems are encountered every day and everywhere. Vagueness is never a new concept to us. It comes from lack of information, in particular, inaccuracy of measurement. Besides, our natural language used for describing / sharing knowledge, communication is a typical embodiment of vagueness. [WINOGRAD, 1972] For example, in contrast to odd numbers, the notion of a beautiful painting is vague, because we are unable to classify uniquely all paintings into two classes: beautiful and not beautiful. Some paintings cannot be decided whether they are beautiful or not by assigning a numerical definition to them. Thus the linguistic description *beauty* is not a precise but a vague concept. Vagueness is inevitable and, at the same time, important. For another example, the color ‘red’ is vague. If you want, it is possible to quantitatively describe ‘red’ by considering the electromagnetic radiation producing it, but in doing so the important human sensation of color, as it happens to be vague, has to be sacrificed. Vagueness is an important source of creativity.

Vagueness exists extensively in psychology, philosophy, literature, law, politics, sociology and other human-oriented fields upon which the precise computing has not shed much light. From the mathematical point of view, the ineffectiveness of precise computing in dealing with vagueness in humanistic systems is a manifestation of what might be called the principle of incompatibility- a principle which asserts that high precision is incompatible with high complexity. [ZADEH, 1972], [ZADEH, 1973] It is suggested that, in order to be able to make significant assertions about the behavior of humanistic systems, it may be necessary to abandon the high standards of rigor and precision that we have expected of our mathematical analyses of well-structured mechanistic systems, and become more tolerant of approaches which are approximate in nature.

In this situation, 'approximate reasoning', by which we mean a mode of reasoning which is neither exact nor very inexact, may offer a more realistic framework for reasoning humanistic systems than the traditional two-valued logic introduced in precise mathematics. It is essentially a methodology for dealing with vague and incomplete knowledge in an approximate or flexible way. [ZADEH, 1979] There are many formal models of approximate reasoning, such as the Bayesian reasoning [PEARL, 1988]; [SHAFER, 1990], fuzzy logics [AMEREL, 1991], non-monotonic logics [SHAFER, 1990], neural networks [LOW, 1993] and rough sets theory [PAWLAK, 1982].

Let us get back to the problem of discourse. In our thesis, we are studying the relations between data obtained from different sensory modalities. A Problem concerning human perception is no doubt a vague system which involves a lot of uncertainty and imprecision. In dealing with vagueness, there are two issues of importance: (1) how to represent vague data, and (2) how to draw inference using vague data. As it is widely agreed, the traditional precise computing methodology is no longer able to efficiently solve these two problems due to its crisp (two-valued) assigning system and strict quantitative logic.

On this premise, in our study, we have put forward a novel approach on the basis of the idea of approximate reasoning to deal with the vagueness embedded in sensory relations. Specifically, the mathematical methodology to be used in the study is developed from the frameworks of rough sets theory and fuzzy sets theory. Then, the above two problems about vagueness are solved in such a way that the fuzzy sets theory helps to normalize or represent the sensory data, and the formulation of the problem or the inference and interpretation of the sensory observations is done principally under the framework of rough sets theory with the core idea being the technique of inclusion degree developed from the rough mereology.

In the following sections, we will give a theoretical introduction to the mathematical frameworks and techniques to be concerned in our proposed approach. To be specific, Section 3.2 describes the basic notions about rough sets theory, rough mereology and inclusion degree; Section 3.3 is an introduction of the fuzzy sets theory including the definition and basic notions of fuzzy sets, fuzzy logic and fuzzy inference; and Section 3.4 is a description of a fuzzy neural network, ANFIS, as a competent modeling method which has high capacity in both data learning and knowledge interpretation.

3.2 Rough sets theory

3.2.1 Knowledge and classification

The theory of knowledge has a long and rich history [RUSSEL, 1950]; [HEMPEL, 1952]; [POPPER, 1959]; [HINTIKKA, 1962]; [HUNT, 1974].

Various aspects of knowledge are widely discussed issues at present, mainly by logicians and Artificial Intelligence (AI) researchers [AIKINS, 1983]; [BOBROW, 1977], [BRACHMAN, 1980], [BRACHMAN, 1986].

Intuitively, knowledge can be perceived as a body of information about some parts of reality, which constitute the specific domain of interest. Knowledge is an information carrier through which we can understand and improve the world we live in. The acquisition, representation and manipulation of knowledge is always of big interest for a variety of scientific domains, such as machine learning, pattern recognition, decision support systems, expert systems and so forth.

According to different theory or methodology, the definition of knowledge is different. In the current thesis, we adopt the one which has been widely accepted that knowledge consists of a family of various classification patterns of a domain of interest, which provide explicit facts about reality –together with the reasoning capacity able to deliver implicit facts derivable from explicit information. [PAWLAK, 1982]

Thus, classification is the core of our understanding of knowledge. In fact, it is well known that knowledge is deep-seated in the classificatory abilities of human beings and even other species. For example, knowledge about the environment is primarily manifested as an ability to classify a variety of situations from the point of view of survival in the real world. Complex classification patterns of sensor signals probably form fundamental mechanisms of every living being. Classification, on more abstract levels, seems to be a key issue in reasoning, learning and decision making, not to mention that in science of classification it is of primary importance.

In this sense, it is claimed that knowledge is necessarily connected with the variety of classification patterns related to specific parts of the real or abstract world, called here the universe of discourse (in short the universe).

Suppose we are given a finite set $U \neq \varnothing$ (the universe) of objects we are interested in. Any subset $X \subseteq U$ of the universe will be called a concept or category in *U* and any family of concepts in *U* will be referred to as knowledge about *U*. And the concepts form a partition or classification of the universe *U*, i.e., in families $C=\{X_1,X_2,\cdots,X_n\}$, such that $X_i \subseteq U$, $X_i \neq \varnothing$, $X_i \cap X_j = \varnothing$ for $i \neq j$, *i*, *j*=1, …, *n* and $\bigcup X_i = U$. Usually we will deal, not with a single classification, but which some families of classifications over *U*. A family of classifications over *U* is called a knowledge base over *U*. Hence, knowledge base represents a variety of classifications of the object of interest. By object we mean anything we can think of, for example, real things, states, abstract concepts, processes, moments of time, etc. It is defined that each single category (or concept) is called an elementary category (concept), and several elementary categories (or concepts) constitute a basic category (or concept).

For better understanding, suppose we are given the following set of hats,

$U=\{x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8\}$. Assume that these hats have different colors (red, green, yellow), types (beret, baseball, fisherman) and materials (cotton, wool). For example a hat can be a yellow cotton fisherman or a green wool baseball, etc.

The set of hats U can be classified according to color, type and material, for example as show below.

hats

x_1, x_3, x_7	- are red,
x_2, x_4	- are green,
x_5, x_6, x_8	- are yellow,

hats

x_1, x_5	- are beret,

x_2, x_6 - are baseball,

x_3, x_4, x_7, x_8 - are fisherman,

and hats

x_2, x_7, x_8 - are cotton,

x_1, x_3, x_4, x_5, x_6 - are wool.

By these classifications we defined three equivalence relations, R_1, R_2 and R_3, having the following equivalence classes

$$U / R_1 = \{\{x_1, x_3, x_7\}, \{x_2, x_4\}, \{x_5, x_6, x_8\}\}$$

$$U / R_2 = \{\{x_1, x_5\}, \{x_2, x_6\}, \{x_3, x_4, x_7, x_8\}\}$$

$$U / R_3 = \{\{x_2, x_7, x_8\}, \{x_1, x_3, x_4, x_5, x_6\}\}$$

which are elementary concepts (categories) in our knowledge base (denoted by K)
$K=(U, \{R_1, R_2, R_3\})$.

Basic categories are set theoretical intersections of elementary categories. For example sets

$$\{x_1,x_3,x_7\}\cap\{x_3,x_4,x_7,x_8\}=\{x_3,x_7\}$$

$$\{x_2,x_4\}\cap\{x_2,x_6\}=\{x_2\}$$

$$\{x_5,x_6,x_8\}\cap\{x_3,x_4,x_7,x_8\}=\{x_8\}$$

are {R1, R2} – basic categories ‘red fisherman’, ‘green baseball’ and ‘yellow fisherman’, respectively. Sets

$$\{x_1,x_3,x_7\}\cap\{x_3,x_4,x_7,x_8\}\cap\{x_2,x_7,x_8\}=\{x_7\}$$

$$\{x_2,x_4\}\cap\{x_2,x_6\}\cap\{x_2,x_7,x_8\}=\{x_2\}$$

$$\{x_5,x_6,x_8\}\cap\{x_3,x_4,x_7,x_8\}\cap\{x_2,x_7,x_8\}=\{x_8\}$$

are exemplary $\{R_1, R_2, R_3\}$ – basic categories ‘red cotton fisherman’, ‘green cotton baseball’ and ‘yellow cotton fisherman’, respectively. Sets

$$\{x_1,x_3,x_7\}\cup\{x_2,x_4\}=\{x_1,x_2,x_3,x_4,x_7\}$$

$$\{x_2,x_4,\}\cup\{x_5,x_6,x_8\}=\{x_2,x_4,x_5,x_6,x_8\}$$

$$\{x_1,x_3,x_7\}\cup\{x_5,x_6,x_8\}=\{x_1,x_3,x_5,x_6,x_7,x_8\}$$

are $\{R_1\}$- categories ‘red or green’, ‘green or yellow’, ‘red or yellow’, respectively.
Note that some categories are not available in this knowledge base. For example sets

$$\{x_2,x_4\}\cup\{x_1,x_5\}=\varnothing$$

$$\{x_1, x_3, x_7\} \cup \{x_2, x_6\} = \varnothing$$

are empty which means that categories ‘green beret’ and ‘red baseball’ do not exist in our knowledge base (are empty categories).

The above example is a simple illustration of the basic notions about knowledge and knowledge representation. The way of dealing with knowledge from classification perspective is the fundamental idea of rough sets theory.

3.2.2 Crisp sets

As was stated by the creator of set theory, George Cantor [CANTOR, 1883], a set is a collection of any objects, which according to some law can be considered as a whole. All mathematical objects, e.g. relations, functions, numbers, etc., are some kind of sets.

In classical set theory a set is uniquely determined by its elements. In other words, it means that every element must be uniquely classified as belonging to the set or not.

Suppose $A = \{a_1, a_2, a_3, a_4, \ldots, a_n\}$ is a cantor’s set. if the elements a_i ($i = 1, 2, 3, \ldots, n$) are subset of universal set X, then set A can be represented for all elements $x \in X$ by its characteristic function

$$\mu_A(x) = \begin{cases} 1 & \text{if } x \in X \\ 0 & \text{if otherwise} \end{cases}$$

In this function, it is assumed that a value of 1 is for those elements x that are belong to set A, and a value of 0 is for those elements x that do not belong to set A.

Thus here the notion of a set is a crisp (precise) one. In mathematics we have to use crisp notions, otherwise precise reasoning would be impossible.

However, as was mentioned in the above context, in our real world, there are a lot of problems dealing with vague concepts. In this situation, the classical two-valued logic is no longer effective. There are two successful theories dealing with vagueness. One is fuzzy set theory according to which sets are defined by partial membership, in contrast to crisp membership used in classical definition of a set. The other approach is rough set theory which expresses vagueness by employing a boundary region of a set.

3.2.3 Rough sets

Rough set theory was developed by Zdzislaw Pawlak in the early 1980's. [PAWLAK, 1982] It is a relatively new soft computing tool for solving problems of vagueness. Nowadays, rough set approach has become a popular mathematical framework in many research areas such as data mining, knowledge discovery from database, decision support, feature selection and pattern recognition. [PAWLAK, 1998]; [PAWLAK, 2007]; [QIAN, 2007]

The rough set approach to data analysis has many important advantages such as it can (i) provide efficient algorithms for finding hidden patterns in data; (ii) generate sets of decision rules from data; (iii) offer straightforward interpretation of obtained results, and so forth.

In the following context, we are going to introduce some basic notions about rough sets.

3.2.3.1 Indiscernibility

A basic assumption in rough set philosophy is that every object of the universe of discourse is associated with some information (data, knowledge). Objects characterized by the same information are *indiscernible* (*similar*) with the available knowledge about them. The *indiscernibility relation* generated in this way is the mathematical basis of rough set theory. Any set of all indiscernible objects is called an elementary set, and expresses a basic granule of knowledge about the universe of discourse. Any union of some elementary sets is referred to as a crisp (precise) set, otherwise the set is rough (imprecise). In other words, a crisp set expresses knowledge that can be subdivided into all discernible granules, whereas a rough set cannot be precisely characterized with available knowledge, or contains knowledge that cannot be decisively subdivided or discerned. Since rough sets theory addresses granularity of knowledge, expressed by the indiscernibility relation, we are unable to deal with single objects but we have to consider clusters of indiscernible objects, as fundamental concepts of the theory.

3.2.3.2 Information system and decision table

From the above remarks, we know that rough set theory in fact deals with the classificatory analysis of information (data, knowledge). A rough-set-based data analysis starts from a data table, called an information system.

Formally, an information system is a pair $S = (U, A)$, where,

- U is a non-empty finite set of objects, or the universe;
- A is a non-empty finite set of attributes; and
- for every $a \in A$, there is a mapping a: $U \rightarrow V_a$, where V_a is called the value set of a.

Any subset of attributes $P \subseteq A$ determines a binary *indiscernibility relation* $IND(P)$ defined by

$$IND(P) = \{(u,v) \in U \times U \mid \forall a \in P, a(u) = a(v)\},$$

Obviously, $IND(P)$ is an equivalence relation on the set U. For $P \subseteq A$, the relation $IND(P)$ constitutes a partition of U, which is denoted by $U/IND(P)$, or just U/P. An information system in which values of all attributes for all objects from U are known is called complete, otherwise it is incomplete.

If an information system is distinguished into two disjoint classes of attributes, named condition and decision attributes, respectively, then the system will be called a decision table and will be denoted by $S = (U, C \cup D)$, in which C and D are disjoint sets of condition and decision attributes, respectively.

Here we give a small example to illustrate the decision table. We consider the price table of diamond as a decision table with eight cases. Two important criteria, color and cut, are selected as the condition attributes, each having three status. Thus the price is the decision attribute which has three levels, high, medium and low. The decision table is show in Table 3-1.

Table 3 - 1 An example of decision table (appraisal system of diamond)

Rule	Color	Cut	Price
u_1	Colorless	Excellent	High
u_2	Colorless	Good	High
u_3	Colorless	Poor	Low
u_4	Faint	Good	High
u_5	Faint	Good	Medium
u_6	Faint	Poor	Low
u_7	Light	Good	Medium
u_8	Light	Poor	Low

It is noticed that cases u_3 and u_4 have exactly the same values of conditions, but different outcomes (different values of decision attribute). Thus, it is revealed that the listed two criteria are not sufficient for judging the quality of a diamond. (Actually, the other important criteria are clarity and carat). In this sense, these two cases are called indiscernible using the available attributes.

A decision table can be complete or incomplete according to whether there exist unknown values on the attributes. In the current study, the sensory data were obtained from standardized experiments, so only complete decision tables are concerned during our analysis.

3.2.3.3 Approximation

Just like in the previous example, the diamonds with high price cannot be defined crisply using the criteria in Table 3-1. The problematic diamonds are cases u_3 and u_4. In other words, it is not possible to induce a crisp (precise) description of such diamonds from the table. And it is here the notion of rough set emerges. Although we cannot define those diamonds crisply, it is possible to delineate the diamonds that certainly have a positive outcome, the diamonds that certainly do not have a positive outcome and, finally, the diamonds that belong to a boundary between the certain cases. This is the so-called approximation.

Let $S = (U, A)$ be an information system and let $B \subseteq A$ and $X \subseteq U$. We can approximate X using only the information contained in B by constructing the *B-lower* and *B-upper approximations* of X, denoted $\underline{B}X$ and $\overline{B}X$ respectively, where $\underline{B}X = \{x \mid [x]_B \subseteq X\}$ and $\overline{B}X = \{x \mid [x]_B \cap X \neq \varnothing\}$. Figure 3-1 shows an illustration of approximation.

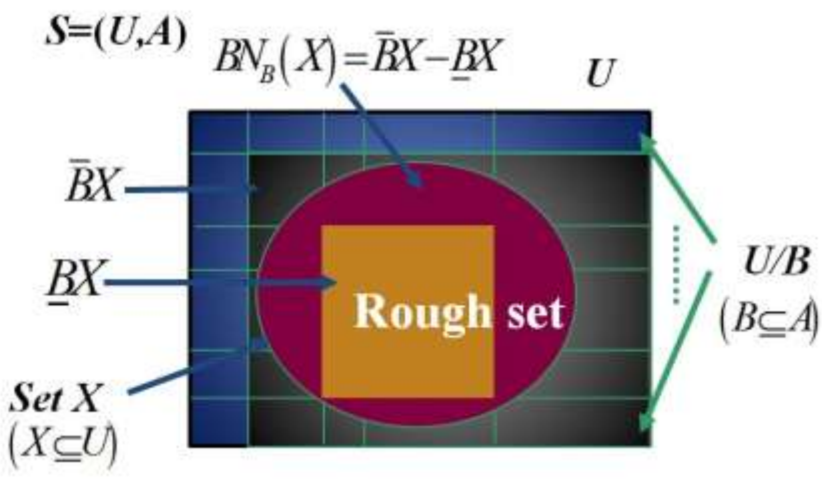


Figure 3 - 1 Approximation

As we can see, the whole square is the universe, the center purple ellipse represents the set *X* to be approximated, or we can say the knowledge to be learned. The orange square represents the set of elements which are with certainty classified into *X* with the knowledge provided by *B*, and this area is called the lower- approximation of *X* denoted by $\underline{B}X$. The elements in the blue square are classified as possible members of *X*, and this square is called the upper approximation of *X* represented by $\overline{B}X$. With the lower and upper approximation, we can define the boundary region $BN_B = \overline{B}X \Leftrightarrow \underline{B}X$, which consists of the elements that we cannot decisively classify into set *X* on the basis of knowledge *B*. the set $U \Leftrightarrow \overline{B}X$ is called *B*-outside region of *X* and consists of those elements which can be with certainty classified as do not belong to *X* (on the basis of knowledge *B*). If the boundary region is non-empty, we call this set a rough set, otherwise, a crisp set.

In the previous example, let $P = \{x \mid Price\ (x) = High\}$, as given by Table x. We then obtain the approximation regions, $\underline{A}P=\{u_1,u_2\}$, $\overline{A}P=\{u_1,u_2,u_4\}$, $BN_A(P) = \{u_4\}$, and $U \Leftrightarrow \overline{A}P=\{u_3,u_5,u_6,u_7,u_8\}$. It follows that the outcome price is rough since the boundary region is not empty.

According to rough set theory, approximation has the following properties:

3.2.4 Rough mereology

As was discussed above, rough set analysis of vague concepts begins with the idea of saturation by classes of indiscernibility. And it solves problems with the idea of approximation. On this basis, there are two points deserving attention:

(i) Definable concepts are unions of atomic concepts: indiscernibility classes.

(ii) Non-definable concepts are approached with definable ones by means of containment, which is the idea of approximation.

Actually, both the operations above are particular cases of general constructs of mereology: the union of sets is a particular class operator and containment is a particular ingredient relation. It follows that setting the rough set context in the realm of mereology will help to obtain a more general and formally adequate means of analysis of vagueness on the lines of rough set theory.

After having a basic understanding of the rough sets, here we are going to introduce the theoretical background from which the inclusion degree, the principal idea of our approach, is originated.

3.2.4.1 Leśniewski's mereology

Mereology is such a theory that it is based on the notion of containment or part-whole relation. It was proposed by Stanislaw Leśniewski [LESNIEWSKI, 1916, 1992] as originally a scheme to avoid the Russell's antinomy (also known as Russell's paradox) in naive set theory of Cantor [GRIFFIN, 2004]; [KLEMENT, 2010]. In fact, it is the first modern mathematical system dealing with relations of being a (proper) part.

We consider a finite set *U*, we assume that *U* is nonempty. A binary relation π on the set *U* will be called the relation of being a (proper) part in the case when the following conditions are fulfilled:

(P1) Irreflexivity. For any $x \in U$, it is not true that $x \pi x$;

(P2) Transitivity. For any triple $x,y,z \in U$, if $x \pi y$ and $y \pi z$, then $x \pi z$.

The notion of being (possibly) an improper part is rendered by the notion of an ingredient. [LESNIEWSKI, 1916, 1992] For objects $x,y \in U$, we say that the object x is a π*-ingredient* of the object y when either $x \pi y$ or x = y. We denote the relation of being a π*-ingredient* by the symbol $ingr(\pi)$. Hence we have:

(i) For $x,y \in U$, $x\, ingr(\pi)\, y$ iff $x \pi y$ or x = y.

It follows immediately from the definition that the relation of being an ingredient has the following properties:

(ii) Reflexivity. For any $x \in U$, we have $x\, ingr(\pi)\, x$.

(iii)Weak antisymmetry. For any pair $x,y \in U$, if $x\, ingr(\pi)\, y$ and $y\, ingr(\pi)\, x$, then $x = y$.

(iv)Transitivity. For any triple $x,y,z \in U$, if $x\, ingr(\pi)\, y$ and $y\, ingr(\pi)\, z$, then $x\, ingr(\pi)\, z$.

We call any pair (U,π) where *U* is a finite set and π a binary relation on the set *U* which satisfies conditions (P1) and (P2) a premodel of mereology.

For a given premodel (U,π) of mereology and a property *m* which can be attributed to objects in *U*, we well say that an object *x* is an object m (*x object m*, for short) when the object *x* has the property *m*. the property *m* will be said to be nonvoid when there exists an object $x \in U$ such that *x object m*. Consider a nonvoid property *m* of objects in a set *U* where (U,π) is a premodel of mereology.

An object $x \in U$ is said to be a set of objects with the property m when the following condition is fulfilled:

(v) For any $y \in U$, if *y object m* and $y\, ingr(\pi)\, x$, then there exist $z,t \in U$ with the properties $z\, ingr(\pi)\, y$, $z\, ingr(\pi)\, t$, $t\, ingr(\pi)\, x$, and *t object m*.

We use the symbol *x set m* to denote the fact that an object *x* is a set of objects with the property *m*.

Assume that *x set m*. if, in addition, the object *x* satisfies the condition

(i) For any $y \in U$, if *y object m* then $y\, ingr(\pi)\, x$.

then we say that the object *x* is a class of objects with the property *m*, and we denote this fact by the symbol *x class m*.

A pair (U,π) is defined to be a model of mereology when it is a premodel of mereology and the following condition holds:

(ii) For any nonvoid property *m* of objcets in the set *U*, there exists a unique object *x* such that *x class m*.

We denote, for an object $x \in U$, by the symbol $ingr(x)$ the property of being an ingredient of *x*, and for a property *m*, we denote by the symbol *s*(*m*) the property of being a set of objects with the property *m*. The fundamental mathematical properties of the mereology of Leśniewski are described in the following.

For any $x \in U$,

(i) $x\, class\big(ingr(x)\big)$;

(ii) $x\, class\big(s(m)\big)$ *iff* $x\, class\, m$;

(iii) $x\, set\big(s(m)\big)$ *iff* $x\, set\, m$.

The above is a brief introduction to the basic notions about Leśniewski's mereology, which is necessary for its further development in the domain of rough sets theory.

3.2.4.2 Rough mereology and inclusion degree

The notion of partial containment constitutes the basic of the so-called rough mereology developed by Lech Polkowski and Andrzej Skowron (Polkowski, Skowron, 1994). In fact, Rough mereology can be regarded as on the one hand a far-reaching generalization of mereology of

Leśniewski [LESNIEWSKI, 1916, 1992], and on the other hand a new point of view of introducing methods of merelogy into rough set data analysis. Rough mereology replaces the relation of being a (proper) part with a hierarchy of relations of being a part in a degree. The formal treatment of partial containment is provided by the notion of rough inclusion, [POLKOWSKI, 1994 (a), (b)]; [POLKOWSKI, 1995] which is constructed as most general functional object conveying the intuitive meaning of the relation of being a part in a degree.

According to rough mereology, the standard rough inclusion is defined as follows.

Let $(X,\le)$ be a poset (i.e., partially ordered set) characterized by the following properties:

(i) $x \le x$ (reflexive)

(ii) $x \le y, y \le x \Rightarrow x = y$ (antisymmetric), and

(iii) $x \le y, y \le z \Rightarrow x \le z$ (transitive)

If, for any $x, y \in X$, there is a real number $D(y/x)$ which can make the following conditions hold:

(i) $0 \le D(y/x) \le 1(x, y \in X)$;

(ii) $x \le y \Rightarrow D(y/x) = 1(x, y \in X)$;

(iii) $z \le x \le y \Rightarrow D(z/y) \le D(z/x)(x, y, z \in X)$; and

(iv) $x \le y \Rightarrow \forall z \in X, D(x/z) \le D(y/z)(x, y \in X)$,

then *D* is called an inclusion degree on *X*.

On this basis, let *X*, *Y* be two finite sets. If $X \subseteq Y$, then we say that *X* is included in *Y*, or *X* is consistent with respect to *Y*. Thus, the inclusion degree $D(Y/X)$ is defined as follows.

$$D(Y/X) = \frac{|X \cap Y|}{|X|} \tag{3-1}$$

3.2.4.3 Consistency degree of decision table

Consider a complete decision table $S=(U, C \cup D)$, in which U is the universe, C a condition attribute set and D a decision attribute set. $X \in U/C$ and $U/D=\{[u]_D : u \in U\}$ are corresponding equivalence classes.

The notion of consistency degree is originally introduced by Pawlak. [PAWLAK, 1991] With regards to a decision table, the consistency degree expresses the percentage of objects (or elements) which can be correctly classified to decision classes of U/D by the condition attribute set C.

Here, in the context of rough mereology, the consistency degree is constructed based on the inclusion degree discussed in the previous section (Eq. (3-1)).

In the above decision table $S=(U,C\bigcup D)$, for any object $u\in U$, the inclusion degree of X into $[u]_D$ is denoted by

$$Inc\left([u]_D/X\right)=\frac{\left|X\bigcap[u]_D\right|}{|X|} \tag{3-2}$$

where $0\le Inc\left([u]_D/X\right)\le 1$.

In fact, this formulation of inclusion degree is in agreement with that of the rough membership function of u in X, i.e., $\delta_X(u)=\frac{\left|X\bigcap[u]_D\right|}{|X|}$ [PAWLAK, 1982], defined according to rough sets theory. This well proves the fact that rough mereology is a good integration of the ideas of mereology and rough sets theory.

It is evident that, if $Inc\left([e_k]_D/X_i\right)=1$, then X can be said to be consistent with respect to $[u]_D$, or one has $X\subseteq[u]_D$. In other words, if X is a consistent set with respect to $[u]_D$, then one has $X\subseteq[u]_D$ (which is called a complete inclusion).

On this basis, we have the first definition about consistency degree.

Definition 1. Let $S=(U,C\bigcup D)$ be a complete decision table, $X\in U/C$ an equivalence class, and $U/D=\left\{[u]_D:u\in U\right\}$. The consistency degree of X with respect to D is defined as

$$Cons(X,D)=1-\frac{4}{|U|}\sum_{i=1}^{|U|}Inc\left([u_i]_D/X_i\right)\left(1-Inc\left([u_i]_D/X_i\right)\right) \tag{3-3}$$

where $0\le Cons(X,D)\le 1$, $Inc\left([u_i]_D/X_i\right)$ is the inclusion degree of X_i with respect to $[u_i]_D$.

Further on, with regards to the consistency measure with respect to a complete decision table, we have the following definition.

Definition 2. Let $S=(U,C\cup D)$ be a complete decision table, $U/C=\{X_1,X_2,\ldots,X_m\}$ an equivalence class, and $U/D=\{[u]_D:u\in U\}$. A consistency measure of C with respect to D is defined as

$$Cons(C,D)=\sum_{j=1}^{m}\frac{|X_j|}{|U|}\left(1-\frac{4}{|U|}\sum_{i=1}^{|U|}Inc\left([u_i]_D/X_i\right)\left(1-Inc\left([u_i]_D/X_i\right)\right)\right) \tag{3-4}$$

where $Inc\left([u_i]_D/X_i\right)$ is the inclusion degree of X_i with respect to $[u_i]_D$.

The mechanism of the consistency measure is illustrated by the following example.

Example. Consider the descriptions of several cars in Table 3-2 [KRYSZKIEWICZ, 1999].

This is a complete decision table, where U = {u_1, u_2, u_3, u_4, u_5, u_6}, C = {Price, Mileage, Size, Max-speed} are the condition attributes and D = {d} is the decision attribute.

Table 3 - 2 A complete decision table about car

Car	Price	Mileage	Size	Max-speed	d
u_1	High	Low	Full	Low	Good
u_2	Low	High	Full	Low	Good
u_3	Low	Low	Compact	Low	Poor
u_4	High	High	Full	High	Good
u_5	High	High	Full	High	Excellent
u_6	Low	High	Full	Low	Good

By computing, one can obtain that

U/C = {{u_1}, {u_2, u_6}, {u_3}, {u_4, u_5}} and

U/d = {{u_1, u_2, u_4, u_6}, {u_3}, {u_5}}.

Let X_1 = {u_1}, X_2 = {u_2, u_6}, X_3 = {u_3} and X_4 = {u_4, u_5}. From Eq. (3-2) one has that

$Inc\left([u_1]_D/X_1\right) = Inc\left([u_2]_D/X_1\right) = Inc\left([u_4]_D/X_1\right) = Inc\left([u_6]_D/X_1\right) = 1$, $Inc\left([u_3]_D/X_1\right)=Inc\left([u_5]_D/X_1\right) = 0$;

$Inc\left([u_1]_D/X_2\right) = Inc\left([u_2]_D/X_2\right) = Inc\left([u_4]_D/X_2\right) = Inc\left([u_6]_D/X_2\right) = 1$, $Inc\left([u_3]_D/X_2\right)=Inc\left([u_5]_D/X_2\right) = 0$;

$Inc\left(\left[u_3\right]_D/X_3\right)$ =1, $Inc\left(\left[u_1\right]_D/X_3\right)$ = $Inc\left(\left[u_2\right]_D/X_3\right)$ = $Inc\left(\left[u_4\right]_D/X_3\right)$ = $Inc\left(\left[u_5\right]_D/X_3\right)$ = $Inc\left(\left[u_6\right]_D/X_3\right)$ = 0 and

$Inc\left(\left[u_1\right]_D/X_4\right)$ = $Inc\left(\left[u_2\right]_D/X_4\right)$ = $Inc\left(\left[u_4\right]_D/X_4\right)$ = $Inc\left(\left[u_5\right]_D/X_4\right)$ = $Inc\left(\left[u_6\right]_D/X_4\right)$ = 1/2, $Inc\left(\left[u_3\right]_D/X_4\right)$ = 0.

Therefore,

$$\begin{aligned}
Cons(C,D) &= \sum_{j=1}^{4}\frac{\left|X_j\right|}{6}\left(1-\frac{4}{6}\sum_{i=1}^{6}Inc\left(\left[u_i\right]_D/X_i\right)\left(1-Inc\left(\left[u_i\right]_D/X_i\right)\right)\right)\\
&=\frac{1}{6}(1\text{-}0)+\frac{2}{6}(1\text{-}0)+\frac{1}{6}(1\text{-}0)+\frac{2}{6}\left(1\text{-}\frac{2}{3}\times\frac{1}{2}\times\frac{1}{2}\times 5\right)\\
&=\frac{13}{18}
\end{aligned}$$

Hence, the consistency measure of C with respect to D in Table 3-2 is $\frac{13}{18}$.

3.3 Fuzzy sets theory

3.3.1 An overview

From the foregoing, we know that the entire real world is complex and the complexity arises from vagueness. ‘The closer one looks at a real world problem, the vaguer becomes its solution’ [ZADEH, 1973]. As the complexity of a problem exceeds a certain threshold, the system must necessarily become vague in nature. And with the increasing of complexity, our ability to make precise and yet significant statements about the behaviour of the system diminishes. During this process, there is a rapid decline in the information afforded by traditional mathematical models due to their insistence on precision.

In this situation, fuzzy sets theory, proposed by Lotfi Zadeh in the mid-1960s [ZADEH, 1965], is the first successful approach to dealing with vagueness. The theory is based upon the notion of degrees of adhesion or partial membership. It uses probability to explain if an event will occur by measuring the chance with which a given event is expected to occur. A simple example to illustrate the difference between classical logic (or Boolean logic) and the logic proposed by fuzzy sets theory (or called Fuzzy logic) is that, if the classical logic has only two values expressed as black or white, fuzzy logic is a continuous form of logic that allows to describe the shades of grey.

Compared with traditional system modelling and analysis techniques based on classical logic, fuzzy sets theory managed to characterize the real world in an approximate manner, that is, to model uncertain or ambiguous data by introducing appropriate simplifications and assumptions of its own, i.e., degree of uncertainty.(Figure 3-2 is a simple illustration of the job of a fuzzy logic system.) It has the following strengths as compared with other techniques.

(i) It is conceptually easy to understand. The mathematical concepts behind fuzzy reasoning are very simple. What makes fuzzy easy is the naturalness of its approach and not the far-reaching complexity.

(ii) It is tolerant of imprecise data. Most things are imprecise even on fairly careful inspection. Fuzzy reasoning builds this understanding into the process rather than tacking it onto the end.

(iii) It is based on natural language. The basis for fuzzy logic is the basis for human communication. This point is especially important. Natural language is the carrier of efficient communication. Since fuzzy logic is built atop the structures of qualitative description used in everyday language, fuzzy logic is easy to use.

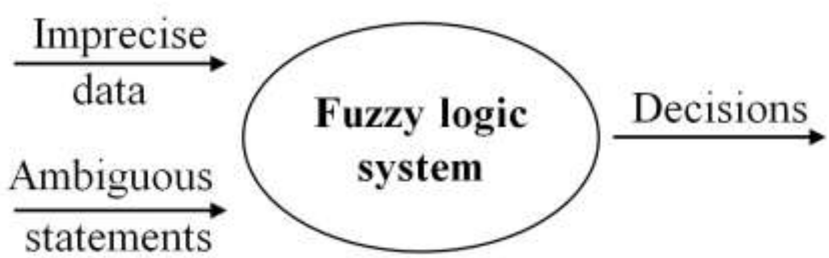


Figure 3 - 2 A fuzzy logic system which accepts imprecise data and ambiguous statements and provides decisions

The first significant development of fuzzy computers is the design of the first first logic chip by Masaki Togai and Hiroyuki Watanabe at Bell Telephone Laboratories. To date, Fuzzy theory has been widely used in control applications including refrigerators, washing machines, cameras and robots, fault and failure diagnosis, image processing, pattern classifying, project planning, fraud detection and in conjunction with neural nets and expert systems. The Japanese use fuzzy logic controllers widely in their consumer goods. Some major applications of fuzzy logic include control algorithms, medical diagnosis, decision-making, economics, engineering, psychology, security and pattern recognition.

Some major areas of fuzzy logic application in the textile industry include classification, grading, diagnosis, planning and control. The main strength of fuzzy logic lies in dealing with uncertainty and imprecision in decision-making processes, an example of which is cotton colour classification. A fuzzy inference system using fuzzy logic to classify major classes of cotton colours has been constructed [ISERMANN, 1998]. A fabric defect identifying system using fuzzy logic has been developed to be able to identify non-defect, slub, nep and composite defects. [MAIERS & SHERIF, 1985], [CHOI, 2001] A method of fuzzy comprehensive evaluation has been investigated for grading fabric softness [CHEN, 2000] An intelligent system based on fuzzy logic has been developed for the fault analysis of sewing machines [STYLIIOS, 1994] Besides, fuzzy logic has also been used in the control of textile processes. An example of such applications is the speed control of looms. A computer program has been developed to simulate the speed control of weaving machines using fuzzy logic [HAHN, 1994]. Moreover, an intelligent system based on the inverse problem of fuzzy comprehensive evaluation has been developed to study the relations between fabric tactile properties and mechanical parameters of a set of suiting fabrics. [XUE, 2009] Some other applications of fuzzy theory in textiles include:

(i) Determination of the handle of fabric with fuzzy cluster analysis [YU, 2008];

(ii) A system for regulating the operation of a spinning machine to optimise its production [PENG, 2004];

(iii) Modelling of colour yield in polyethylene terephthalate dyeing with statistical and fuzzy regression [TAVANAI, 2005]

In our thesis, fuzzy sets theory has been introduced to solve two major problems. On one hand, fuzzy representation and operation techniques have been applied to normalize the sensory data; on the other hand, a fuzzy inference system has been developed to integrate different computing indices. Around these two tasks, in the following context, we are going to present some principal notions about fuzzy sets theory.

3.3.2 Fuzzy sets

3.3.2.1 Definition

As defined in the previous section, the characteristic function of a crisp set assigns a value of either 1 or 0 to each individual in the universal set, thereby discriminating between members and non-members of the crisp set under consideration. [ZADEH, 1965] This function can be generalized such that the values assigned to the elements of the universal set fall within a specified range and indicate the membership grade of these elements in the set in question. Larger values denote higher degrees of set membership. Such a function is called a membership function, and the set defined by it a fuzzy set.

A fuzzy set is thus a set containing elements that have varying degrees of membership in the set. This idea is in contrast with classical or crisp set, because members of a crisp set would not be members unless their membership was full or complete in that set (i.e., their membership is assigned a value of 1). Elements in a fuzzy set, because their membership need not be complete, can also be members of other fuzzy set on the same universe.

The most commonly used range of values of membership functions is the unit interval [0, 1]. In this case, each membership function maps elements of a given universal set X into real numbers in [0, 1].

The membership function of a fuzzy set A can be denoted by μ_A or the same capital letter of the fuzzy set A; that is,

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

or

$$A : X \to [0, 1].$$

Each fuzzy set is completely and uniquely defined by one particular membership function.

As discussed previously, fuzzy sets allow us to represent vague concepts expressed in natural language. The representation depends not only on the concept, but also on the context in which it is used. For example, applying the concept of high temperature in one context to weather and in another context to a nuclear reactor would be represented by very different fuzzy sets.

Even for similar contexts, fuzzy sets representing the same concept may vary considerably. As an example, let us consider four fuzzy sets whose membership functions are shown in Figure 3-3. Each of these fuzzy sets expresses, in a particular form, the general conception of a class of real numbers that are close to 2.

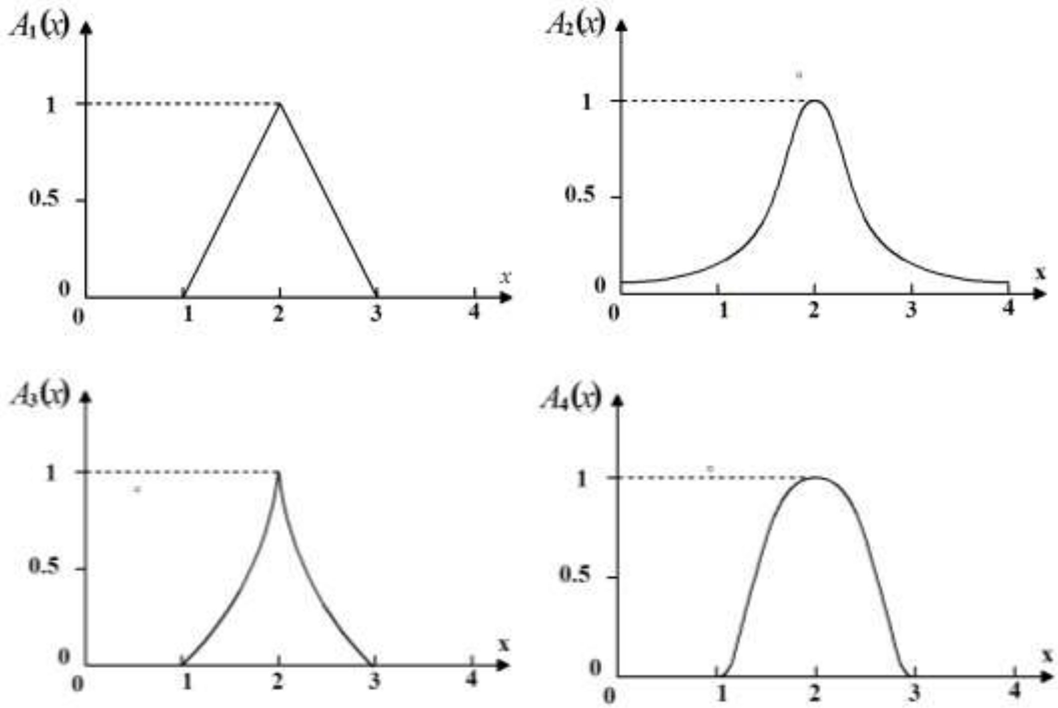


Figure 3 - 3 Different membership functions

In this case, in spite of their differences, the four fuzzy sets are similar in the sense that the following properties are possessed by each $A_i\left(i \in N_4\right)$:

(i) $A_i(2)=1$ and $A_i(x)<1$ for all $x \neq 2$;

(ii) A_i is symmetric with respect to $x = 2$, that is $A_i(2+x)=A_i(2-x)$ for all $x \in U$;

(iii) $A_i(x)$ decreases monotonically from 1 to 0 with the increasing difference $|2-x|$.

The whole concept can be illustrated with the following example. Let us consider the problem of *Age*. *X* is the set of people (or the universe of discourse). A fuzzy set *Young* is defined, which answers the question 'to what degree is person x is *Young*?' To each person in the universe of discourse, we have to assign a degree of membership in the fuzzy set *Young*. We probably have the following membership function.

$$young(x)=\begin{cases} 1, & if \quad age(x) \leq 20, \\ (30\text{-}age(x))/10, & if \quad 20 < age(x) \leq 30, \\ 0, & if \quad age(x) > 30. \end{cases}$$

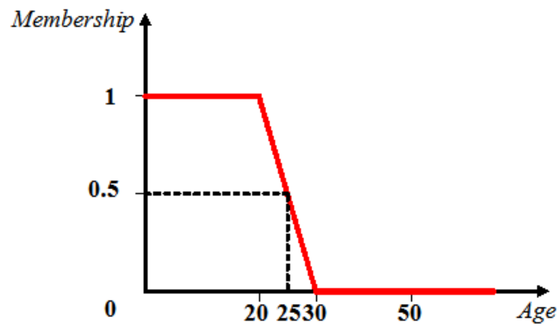


Figure 3 - 4 Membership function of Age

Figure 3-4 shows the graph of this membership function.

On this basis, given a list of people with different ages, their degrees of youth are computed according to the membership function and listed in Table 3-3.

Given this definition, Table 3-3 shows a list of person with different ages and degrees of youth.

Table 3 - 3 People with different ages and their degrees of youth

Person	Age	Degree of youth
Johan	10	1.00
Edwin	20	0.90
Jason	25	0.50
Jay	28	0.20
Anne	83	0.00

So, we would say that the degree of truth of the statement ‘Jason is young’ is 0.50.

3.3.2.2 Fuzzy set operations

Consider three fuzzy sets *A*, *B* and *C* on the universe *X*. For a given element x of the universe, the following fuzzy operations, union, intersection and complement, are defined for *A*, *B* and *C* on *X*:

(i) Union:

$$(A \cup B)(x) = \min\left[A(x), B(x)\right],$$

(ii) Intersection:

$$(A \cap B)(x) = \max\left[A(x), B(x)\right],$$

(iii)Complement:

$$\overline{A}(x) = 1 - A(x)$$

The venn diagram of these operations are shown in Figure 3-5.

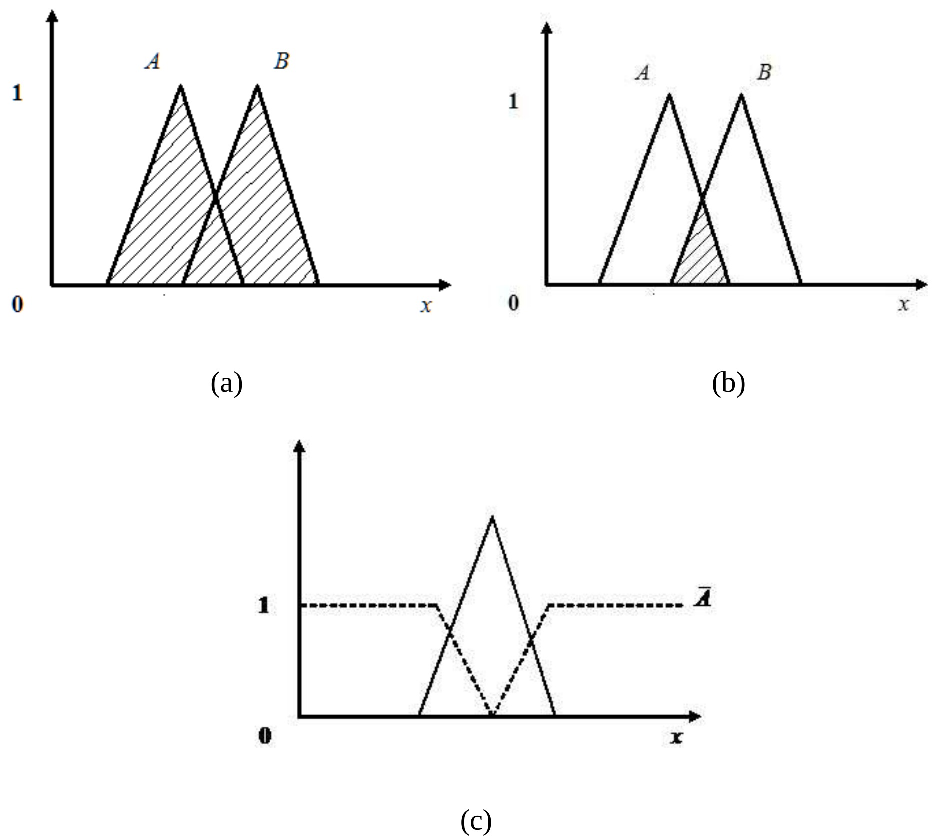


Figure 3 - 5 Venn diagrams of fuzzy operations ((a) union, (b)intersection, (c)complement)

3.3.2.3 Properties of fuzzy sets

Consider three fuzzy sets *A*, *B* and *C* on the universe *X*, the properties of classical set also suits for the fuzzy sets, which include:

(i) Commutativity:

$$A \cup B = B \cup A,$$

$$A \cap B = B \cap A.$$

(ii) Associativity:

$A \cup (B \cup C) = (A \cup B) \cup C$,

$A \cap (B \cap C) = (A \cap B) \cap C$.

(iii) Distributivity:

$A \cup (B \cap C) = (A \cup B) \cap (A \cup C)$,

$A \cap (B \cup C) = (A \cap B) \cup (A \cap C)$

(iv) Indentity:

$A \cup \varnothing = A$ and $A \cap X = A$,

$A \cap \varnothing = \varnothing$ and $A \cup X = X$.

(v) Transtivity:

If $A \subset B \subset C$ then $A \subset C$.

(vi) Involution:

$\overline{\overline{A}} = A$

3.3.2.4 Fuzzy relations

(1) Definition

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].

A fuzzy relation R is a mapping from the Cartesian space $X \times Y$ 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 $\mu_R(x,y)$.

Hence, a fuzzy relation can be expressed as

$R = \{((x,y), \mu_R(x,y)) | (x,y) \in X \times Y\}$.

(2) Operations on fuzzy relations

Let R and T be fuzzy relations on Cartesian space $X \times Y$. Then we define the following operations:

(i) Union

The union of two fuzzy relations R and T is defined as,

$\forall(x,y) \in X \times Y$

$$\mu_{R \cup T}(x,y) = \max(\mu_R(x,y), \mu_T(x,y))$$
$$= \mu_R(x,y) \vee \mu_T(x,y)$$

In practice, '$\vee$' is generally realized using a MAX operation. For *n* relations, we extend it to the following form:

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

(ii) Intersection

The intersection of two fuzzy relations *R* and *T* is defined as,

$\forall(x,y) \in X \times Y$

$$\mu_{R \cap T}(x,y) = \min(\mu_R(x,y), \mu_T(x,y))$$
$$= \mu_R(x,y) \wedge \mu_T(x,y)$$

'$\wedge$' is usually realized using MIN operation. In the same manner, the intersection relation for *n* fuzzy relations is defined as

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

(iii)Complement

The complement relation $\overline{R}$ of the fuzzy relation R is defined by

$\forall(x,y) \in X \times Y$

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

(3) Composition of fuzzy relations

Let R be a fuzzy relation on the Cartesian space $X \times Y$, S be a fuzzy relation on $Y \times Z$, and T be a fuzzy relation on $X \times Z$. The most often used composition method is called max-min composition. Thus, we have

$$T = R \circ S$$
$$= \left\{ (x,z), \max_y \left\{ \min(\mu_R(x,y), \mu_S(x,y)) \right\} \Big/ x \in X, y \in Y, z \in Z \right\}$$

The above is the set-theoretic notation. In function-theoretic form, we have

$$\mu_T(x,\mathrm{z}) = \underset{y \in Y}{\vee} \left(\mu_R(x,\mathrm{y}) \wedge \mu_S(\mathrm{y},\mathrm{z}) \right)$$

3.3.2 Fuzzy reasoning

According to classical logic, every proposition (e.g., conclusion or decision) is either true or false. But as we have discussed a lot in the above context, many propositions in the real world are both partially true and partially false. Consider the following deductive inference,

(i) Everyone who is 40 to 70 years old is old but is very old if he (she) is 71 years old or above; everyone who is 20 to 39 years old is young but is very young if he (she) is 19 years old or below.

(ii) David is 40 years old and Mary is 39 years old.

(iii) David is old but not very old; Mary is young but not very young

This is a typical example of approximate reasoning that cannot be handled by classical (precise) reasoning using two-valued logic, but this deductive inference is meaningful in our daily life. In fact, classical reasoning is often questioned, especially in humanistic fields. In this situation, multi-valued logics have been proposed and developed to extend and generalize the classical logic. Three-valued and *n*-valued logics (or called Lukasiewicz's logic) emerged successively. [GILES, 1976] It has turned out that these logics are successful both logically and mathematically to solve specific problems. The ultimate generalization of the classical logic is the infinite-valued logic – fuzzy logic, defined by Zadeh on the basis of Lukasiewicz's *n*-valued logic.

Compared with classical logic, fuzzy logic allows the imprecise linguistic terms such as:

(i) fuzzy predicates: old, rare, severe, expensive, high, fast

(ii) fuzzy quantifiers: many, few, usually, almost, little, much

(iii) fuzzy truth values: very true, true, unlikely true, mostly false, false, definitely false

According to fuzzy logic, the above example about age can be well reasoned.

In the following context, we will give a brief introduction to the basic notions about fuzzy logic, including the mathematical description and fuzzy rules, and fuzzy inference system.

3.3.2.1 Fuzzy logic and fuzzy rules

(1) Fuzzy logic operations

Fuzzy logic provides foundations for approximate reasoning using imprecise propositions based on fuzzy set theory, in a way similar to the classical reasoning using precise propositions based on the classical set theory. Fuzzy logic is isomorphic to the fuzzy set theory that employs the min, max, and 1-a operation for fuzzy set intersection, union, and complement, respectively.

To describe fuzzy logic mathematically, we introduce the following concepts and notation.

Let S be a universe and A a fuzzy set associated with a membership function, $\mu_A(x)$, $x \in S$. If $y=\mu_A(x_0)$ is a point in [0, 1], representing the truth value of the proposition 'x_0 is a' or simply 'a', then the truth value of 'not a' is given by

$$\bar{y}=\mu_A(x_0 \text{ is not } a)=1\text{-}\mu_A(x_0 \text{ is } a)=1\text{-}\mu_A(x_0)=1\text{-}y.$$

Consequently, for n members $x_1, \ldots, x_n$ in S with n corresponding truth values $y_i=\mu_A(x_i)$ in [0, 1], $i = 1, \ldots, n$, the *truth values* of 'not a' is defined as

$$\overline{y_i}=1\text{-}\,y_i \quad i = 1, \ldots, n.$$

With n > 3, we define the logical operations and, or, not, implication, and equivalence as follows : for any $a,b \in S$,

$$\mu_A(a \wedge b)=\mu_A(a) \wedge \mu_A(b)=\min\{\mu_A(a),\mu_A(b)\};$$

$$\mu_A(a \vee b)=\mu_A(a) \vee \mu_A(b)=\max\{\mu_A(a),\mu_A(b)\};$$

$$\mu_A(\bar{a})=1\text{-}\,\mu_A(a);$$

$$\mu_A(a \Rightarrow b)=\mu_A(a) \Rightarrow \mu_A(b)=\min\{1, 1+\mu_A(b)\text{-}\,\mu_A(a)\};$$

$$\mu_A(a \Leftrightarrow b)=\mu_A(a) \Leftrightarrow \mu_A(b)=1\text{-}\left|\mu_A(a)\text{-}\,\mu_A(b)\right|.$$

For multi-point cases, e.g., $a_i, b_j \in S$, with $\mu_A(a_i)$, $\mu_A(b_j) \in [0,1]$, $i = 1, \ldots, n$, $j = 1, \ldots, m$, where $1 \le n,m \le \infty$, we can define

$$\mu_A(a_i,\ldots,a_n) \wedge \mu_A(b_i,\ldots,b_m) = \max_{1\le i\le n, 1\le j\le m}\left\{\min\left\{\mu_A(a_i),\mu_A(b_j)\right\}\right\}$$

This is equivalent to the minimum between two fuzzy numbers $a \wedge b$. Other operations can be defined accordingly.

(2) Fuzzy IF-THEN rules

The main content of logic is the study of inference rules that allow new logical values to be produced as functions of certain existing variables. [JANG, 1997]

For example, a frequently used inference rule in classical reasoning is:

Modus ponens: $(a \wedge (a \Rightarrow b)) \Rightarrow b$.

This rule is interpreted as

IF ‘*a* is true’ AND the statement ‘IF *a* is true THEN *b* is true’ is true THEN ‘b is true’.

In terms of membership values, this is equivalent to the following:

IF $\mu(a)=1$

AND $\mu(a \Rightarrow b)=\min\{1,1+\mu(b)-\mu(a)\}=\min\{1,\mu(b)\}=1$

THEN $\mu(b)=1$.

In fuzzy logic, for the modus ponens, the inference rule reads the same. We have

$(a \wedge (a \Rightarrow b)) \Rightarrow b$

But in terms of membership values, we have

IF $\mu(a)>0$

AND $\mu(a \Rightarrow b)=\min\{1,1+\mu(b)-\mu(a)\}>0$

THEN $\mu(b)>0$.

This fuzzy logic inference can be interpreted as follows: IF *a* is true with a certain degree of confidence AND “IF *a* is true with a certain degree of confidence THEN *b* is true with a certain degree of confidence” THEN *b* is true with a certain degree of confidence. All these “degrees of confidence” can be quantitatively evaluated by using the corresponding membership functions. This example is a *generalized modus ponens*, called *fuzzy modus ponens*.

In the above fuzzy inference rule, there is a basic relation which is of great importance for fuzzy logic, e.g., the implication relation, $a \Rightarrow b$. It can be interpreted, in linguistic terms, as ‘IF *a* is true THEN *b* is true’. For fuzzy logic performed on a fuzzy set *A*, we have a membership function μ_A describing the truth values of $a \in A$ and $b \in A$. In this case, a more complete linguistic statement would be

‘(IF $a \in A$ is true with truth value $\mu_A(a)$ THEN $b \in A$ is true with a truth value $\mu_A(b)$) has a truth value $\mu_A(a \Rightarrow b)=\min\{1,1+\mu_A(b)-\mu_A(a)\}$.’

In the above, both *a* and *b* belong to the same fuzzy set *A* and share the same membership function μ_A. If they belong to different fuzzy sets *A* and *B* ($a \in A$ and $b \in B$), the implication relation $a \Rightarrow b$ is defined in linguistic terms as

‘IF $a \in A$ is true with a truth value $\mu_A(a)$ THEN $b \in B$ is true with truth value $\mu_B(b)$.’

Or in most cases, such statements can be written in the following simple form:

'IF *a* is *A* THEN *b* is *B*.'

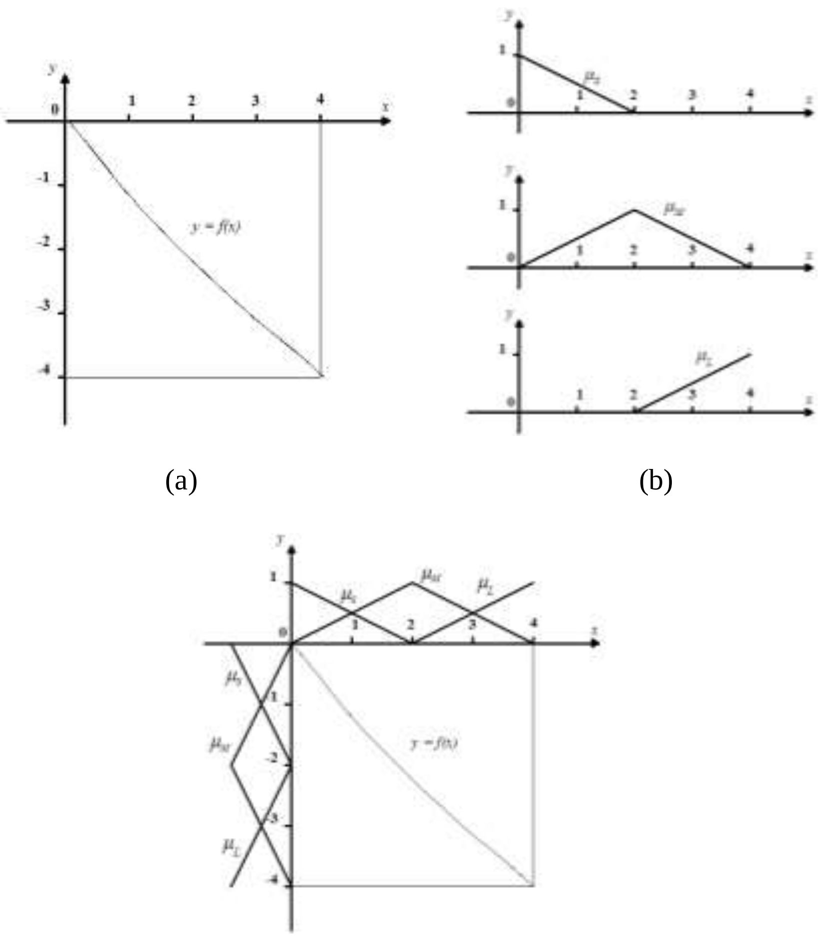
A fuzzy logic implication statement of this form is usually called a *fuzzy IF-THEN rule*.

To be general, let A1, …, An, and B be fuzzy sets with membership functions μ_{A_1}, …, μ_{A_n} and μ_B, respectively.

Definition. A *General Fuzzy IF-THEN Rule* has the form

'IF a_1 is A_1 AND … AND a_n is A_n THEN *b* is *B*'

Here, we give an example to illustrate how the fuzzy IF-THEN rules approximate real functions.



(a) (b)

(c)

Figure 3 - 6 An example of approximating a real function by a fuzzy rule base

Let $y = f(x)$ be a real variable real-valued and invertible function defined on *X* = [0,4] with range *Y* = [–4,0] as shown in Figure 3-6 (a). Suppose that we don't actually know the exact formula of *f*. We let μ_S, μ_M, and μ_L be membership functions defined on *X* and *Y*, describing 'small', 'medium', and 'large' in absolute values, respectively, as shown in Figure 3-6 (b). Thus, we may approximate the real function $y = f(x)$ by the following fuzzy rule base as shown in Figure 3-6 (c):

(i) 'IF x is positive small THEN y is negative small'.

(ii) 'IF x is positive e medium THEN y is negative medium'.

(iii)'IF x is positive large THEN y is negative large'.

Using the brief notation 'a is A' to mean '$a \in A$ has a membership value $\mu_A(a)$' as we did before, one may now rewrite the above three implication statements as follows:

(i) 'IF x is PS THEN y is NS'.

(ii) 'IF x is PM THEN y is NM'.

(iii)'IF x is PL THEN y is NL'.

3.3.2.2 Fuzzy inference system

Fuzzy inference systems (FISs) are also known as fuzzy rule-based systems, fuzzy models, fuzzy expert systems, and fuzzy associative memory. This is a major unit of a fuzzy logic system. The decision-making is an important part in the entire system. The FIS formulates suitable rules and based upon the rules the decision is made. This is mainly based on the concepts of the fuzzy set theory, fuzzy IF–THEN rules, and fuzzy reasoning. [JANG, 1997]; [WANG, 2009]

(1) Construction and working of inference system

Fuzzy inference system consists of a fuzzification interface, a rule base, a database, a decision-making unit, and finally a defuzzification interface. A FIS with five functional block described in Figure 3-7. The function of each block is as follows:

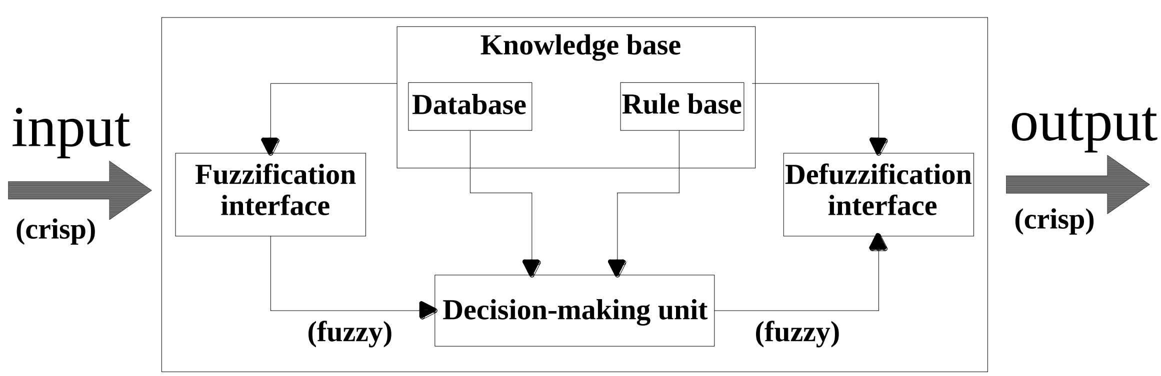


Figure 3 - 7 General structure of a fuzzy inference system

(i) A *rule base* containing a number of fuzzy IF–THEN rules;

(ii) A *database* which defines the membership functions of the fuzzy sets used in the fuzzy rules;

(iii) A *decision-making unit* which performs the inference operations on the rules;

(iv) A *fuzzification interface* which transforms the crisp inputs into degrees of match with linguistic values; and

(v) A *defuzzification interface* which transforms the fuzzy results of the inference into a crisp output.

The working of FIS is as follows. The crisp input is converted in to fuzzy by using fuzzification method. After fuzzification the rule base is formed. The rule base and the database are jointly referred to as the *knowledge base*. Defuzzification is used to convert fuzzy value to the real world value which is the output. The steps of *fuzzy reasoning* (inference operations upon fuzzy IF–THEN rules) performed by FISs are:

(i) Compare the input variables with the membership functions on the antecedent part to obtain the membership values of each linguistic label. (this step is often called *fuzzification*.)

(ii) Combine (through a specific *t*-norm operator, usually multiplication or min) the membership values on the premise part to get *firing strength* (*weight*) of each rule.

(iii) Generate the qualified consequents (either fuzzy or crisp) or each rule depending on the firing strength.

(iv) Aggregate the qualified consequents to produce a crisp output. (This step is called *defuzzification.*)

(2) Fuzzy inference methods

The most important two types of fuzzy inference methods are Mamdani's method and Takagi-sugeno method (TS method in short). The former is the most commonly used inference method which was introduced by Mamdani and Assilian [MAMDANI, 1975]. The latter was introduced by Sugeno [SUGENO, 1985]. The main difference between the two methods lies in the consequent of fuzzy rules. Mamdani fuzzy systems use fuzzy sets as rule consequent whereas TS fuzzy systems employ linear functions of input variables as rule consequent.

In the current study we have employed the Mamdani's inference method to generate a robust system in order to aggregate different computing indices. And the fuzzy-neural network ANFIS which has been developed to model the relations between fabric tactile properties and visual features is based on the principles of TS fuzzy system. So in the following context, we will give detailed introduction to respective methods.

(i) Mamdani's fuzzy inference method

Mamdani's fuzzy inference method is the most commonly seen fuzzy methodology. Mamdani's method was among the first control systems built using fuzzy set theory. It was proposed by Mamdani [MAMDANI, 1975] as an attempt to control a steam engine and boiler combination by synthesizing a set of linguistic control rules obtained from experienced human operators. Mamdani's effort was based on Zadeh's [ZADEH, 1973] paper on fuzzy algorithms for complex systems and decision processes.

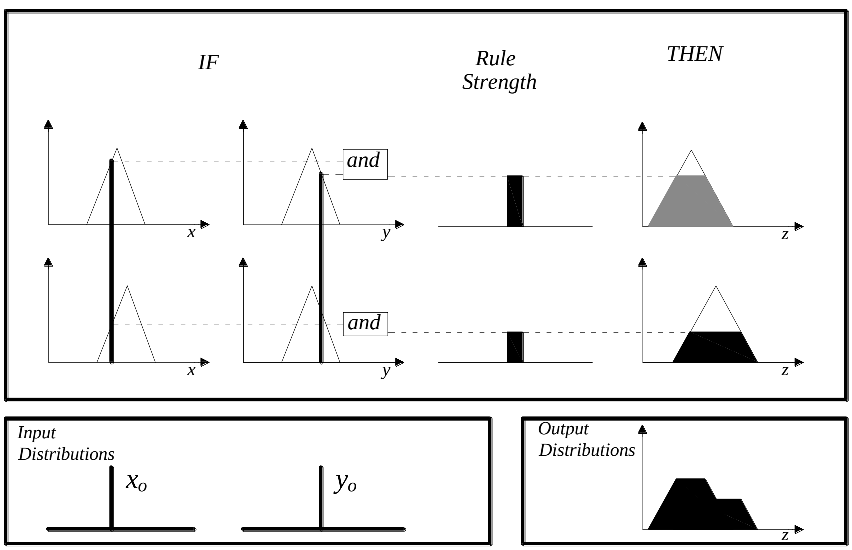


Figure 3 - 8 A two input, two rule Mamdani FIS with crisp inputs

An example of a Mamdani inference system is shown in Figure 3-8. To compute the output of this FIS given the inputs, six steps has to be followed:

a) Determining a set of fuzzy rules
b) Fuzzifying the inputs using the input membership functions
c) Combining the fuzzified inputs according to the fuzzy rules to establish a rule strength

d) Finding the consequence of the rule by combining the rule strength and the output membership function
e) Combining the consequences to get an output distribution
f) Defuzzifying the output distribution (this step is only if a crisp output (class) is needed).

The following is a more detailed description of this process

STEP 1 Creating fuzzy rules

As introduced in the above context, fuzzy rules are a collection of linguistic statements that describe how the FIS should make a decision regarding classifying an input or controling an output.

For example:

'IF temperature is high **AND** humidity is high **THEN** room is hot.'

There would have to be membership functions that define high temperature (input 1), high humidity (input 2), and a hot room (output 1). This process of taking an input such as temperature and processing it through a membership function to determine 'high' temperature is called fuzzification and is discussed in the section 'Fuzzification.'

STEP 2 & STEP 3. Fuzzification

The purpose of fuzzification is to map the inputs from a set of sensors (or features of those sensors such as amplitude or spectrum) to values from 0 to 1 using a set of input membership functions. In the example shown in Figure 3-8, there are two inputs, *x*0 and *y*0 shown at the lower left corner. These inputs are mapped into fuzzy numbers by drawing a line up from the inputs to the input membership functions above and marking the intersection point.

These input membership functions, as discussed previously, can represent fuzzy concepts such as 'large' or 'small,' 'old' or 'young,' 'hot' or 'cold,' etc. For example, x_0 could be the EMG energy coming from the front of the forearm and y_0 could be the EMG energy coming from the back of the forearm. The membership functions could then represent large amounts of tension coming from a muscle or small amounts of tension. When choosing the input membership functions, the definition of large and small may be different for each input.

STEP 4 Consequence

The consequence of a fuzzy rule is computed using two steps:

a) Computing the rule strength by combining the fuzzified inputs using the fuzzy combination process. This is shown in Figure 3-8. In this example, the fuzzy "AND" is used to combine the membership functions to compute the rule strength.
b) Clipping the output membership function at the rule strength.

STEP 5 Combining outputs into an output distribution

The outputs of all of the fuzzy rules must now be combined to obtain one fuzzy output distribution. This is usually, but not always, done by using the fuzzy "OR." Figure 3-8 shows an example of this. The output membership functions on the right-hand side of the figure are combined using the fuzzy OR to obtain the output distribution shown on the lower right corner of the Figure 3-8.

STEP 6 Defuzzification of output distribution

In many instances, it is desired to come up with a single crisp output from an FIS. For example, if one was trying to classify a letter drawn by hand on a drawing tablet, ultimately the FIS would have to come up with a crisp number to tell the computer which letter was drawn. This crisp number is obtained in a process known as defuzzification. There are two common techniques for defuzzifying:

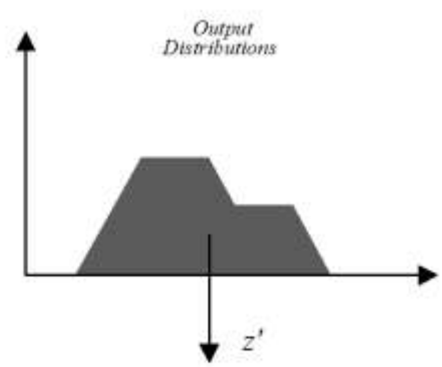


Figure 3 - 9 Defuzzification using the center of mass

a) Center of mass. This technique takes the output distribution and finds its center of mass to come up with one crisp number. This is computed as follows:

$$z = \frac{\sum_{j=1}^{q} Z_j u_c(Z_j)}{\sum_{j=1}^{q} u_c(Z_j)}$$

where z is the center of mass and u_c is the membership in class c at value z_j . An example outcome of this computation is shown in Figure 3-9.

b) Mean of maximum. This technique takes the output distribution and finds its mean of maxima to come up with one crisp number. This is computed as follows:

$$z = \sum_{j=1}^{l} \frac{z_j}{l},$$

where z is the mean of maximum, zj is the point at which the membership function is maximum, and l is the number of times the output distribution reaches the maximum level. An example outcome of this computation is shown in Figure 3-10.

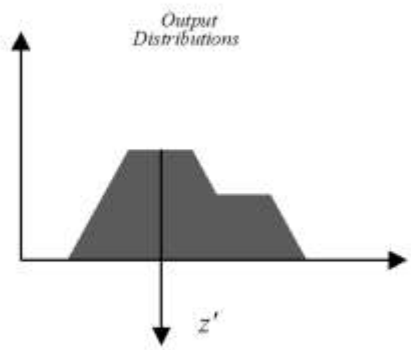


Figure 3 - 10 Defuzzification using the mean of maximum

In practical application, Mamdani method has the following strengths

- It is intuitive.
- It has widespread acceptance.
- It is well suited to human input.

ii) Takagi-sugeno fuzzy inference method (TS method)

The TS fuzzy model was proposed by Takagi, Sugeno, and Kang in an effort to formalize a system approach to generating fuzzy rules from an input-output data set. [SUGENO, 1985] A typical fuzzy rule in a TS model has the format

IF x is A and y is B THEN $z = f(x, y)$,

where A, B are fuzzy sets in the antecedent; $Z = f(x, y)$ is a crisp function in the consequent. Usually $f(x, y)$ is a polynomial in the input variables x and y, but it can be any other functions that can appropriately describe the output of the system within the fuzzy region specified by the antecedent of the rule. When $f(x, y)$ is a first-order polynomial, we have the *first-order* TS fuzzy model. When f is a constant, we then have the *zero-order* TS fuzzy model, which can be viewed either as a special case of the Mamdani FIS where each rule's consequent is specified by a fuzzy singleton.

The first two parts of the fuzzy inference process, fuzzifying the inputs and applying the fuzzy operator, are exactly the same for both methods. The main difference between Mamdani and TS is that the TS output membership functions are either linear or constant. A typical rule in a TS fuzzy model has the form

IF Input 1 = x AND Input 2 = y, THEN Output is $z = ax + by + c$.

For a zero-order TS model, the output level z is a constant ($a = b = 0$).The output level z_i of each rule is weighted by the firing strength w_i of the rule. For example, for an AND rule with Input 1 = x and Input 2 = y, the firing strength is

$$w_i = \text{AndMethod}\left(F_1(x), F_2(y)\right)$$

where $F_{1,2}$ are the membership functions for Inputs 1 and 2. The final output of the system is the weighted average of all rule outputs, computed as

$$\text{Final output} = \frac{\sum_{i=1}^{N} w_i z_i}{\sum_{i=1}^{N} w_i}.$$

A TS rule operates as shown in Figure 3-11.

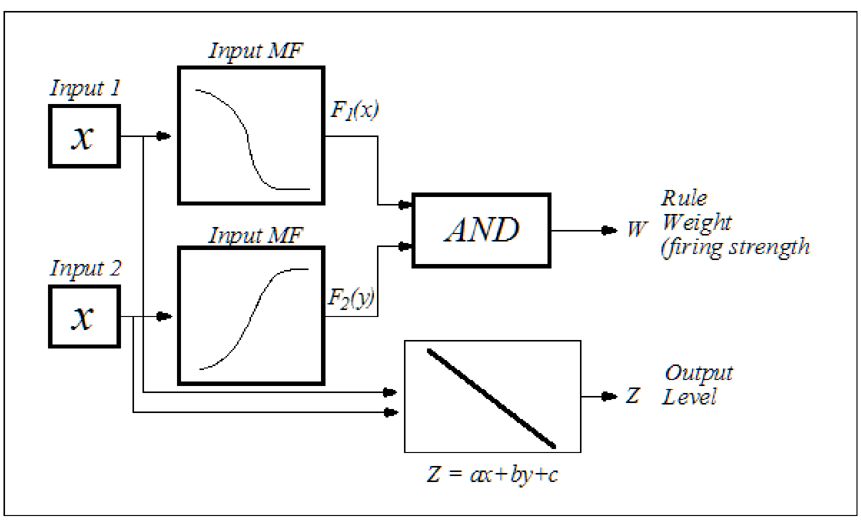


Figure 3 - 11 Takagi-sugeno rule

Because of the linear dependence of each rule on the input variables of a system, the TS method is ideal for acting as an interpolating supervisor of multiple linear controllers that are to be applied, respectively, to different operating conditions of a dynamic nonlinear system. For example, the performance of an aircraft may change dramatically with altitude and Mach number. Linear controllers, though easy to compute and well suited to any given flight condition, must be updated regularly and smoothly to keep up with the changing state of the flight vehicle. A TS FIS is extremely well suited to the task of smoothly interpolating the linear gains that would be applied across the input space; it is a natural and efficient gain scheduler. Similarly, a TS system is suited for modeling nonlinear systems by interpolating between multiple linear models.

Since it is a more compact and computationally efficient representation than a Mamdani system, the TS system lends itself to the use of adaptive techniques for constructing fuzzy models. These adaptive techniques can be used to customize the membership functions so that the fuzzy system best models the data, which is the case for the development of an ANFIS model in our thesis.

To sum up, TS method has the following advantages in practical applications.

(1) It is computational efficient.
(2) It works well with linear techniques (e.g., PID control).
(3) It works well with optimization and adaptive techniques.
(4) It has guaranteed continuity of the output surface.
(5) It is well suited to mathematical analysis.

Fuzzy inference system is the most important modeling tool based on fuzzy set theory. The FISs are built by domain experts and are used in automatic control, decision analysis, and various other expert systems.

3.4 Adaptive network-based fuzzy inference system (ANFIS)

One major task of the current thesis is to model the relations between fabric tactile properties and visual features. Technically, neural network (NN) is one of the most effective and appropriate artificial intelligence tools for pattern recognition. Due to its high capacity in data learning, NN has been well employed in many data-intensive applications where qualitative and complex reasoning is required. But NN has still has its inevitable limitations in solving practical problems, especially humanistic problems. For example, it has no explanation capabilities and it provides a 'black box' approach to problem solving. In this situation, one is wondering what if the network-based technique can be endowed with expert inference capacity. Recently, one popular soft computing method, Adaptive network-based fuzzy inference system (ANFIS) [JANG, 1993]; [JANG, 1995]; [JANG, 1997], has realized this assumption. It is a hybrid combination of artificial networks (ANN) and fuzzy inference system (FIS). Specifically, it represents a neural network approach to the design of fuzzy inference system.

ANFIS provides a useful neural network approach for the solution of function approximation problems. Data driven procedures for the synthesis of ANFIS networks are typically based on clustering a training set of numerical samples of the unknown function to be approximated. Since introduction, ANFIS networks have been successfully applied to classification tasks, rule-based process controls, pattern recognition problems and so forth. ANFIS is a method based on the input-output data of the system under consideration. As mentioned in the previous section, here a fuzzy inference system comprises of the Takagi-sugeno model to formalize a systematic approach to generate fuzzy rules from the input output data set.

In the following, we will briefly introduce the basic structure of an ANFIS system.

For simplification, we assume the predictive model under consideration has two inputs and one output. For a first-order TS fuzzy model, a typical rule set with two fuzzy if-then rules can be expressed as [SUGENO, 1985]:

Rule 1 : If x is A_1 and y is B_1 then $f_1 = p_1x + q_1y + r_1$

Rule 2 : If x is A_2 and y is B_2 then $f_2 = p_2x + q_2y + r_2$

where A_i and B_i are the membership functions for the inputs x and y, respectively, f_i are the outputs within the fuzzy region specified by the fuzzy rule, p_i, q_i and r_i are the design parameters that are determined during the training process. The ANFIS architecture to implement these two rules is shown in Figure 3-12, in which a circle indicates a fixed node, whereas a square indicates an adaptive node [JANG, 1993].

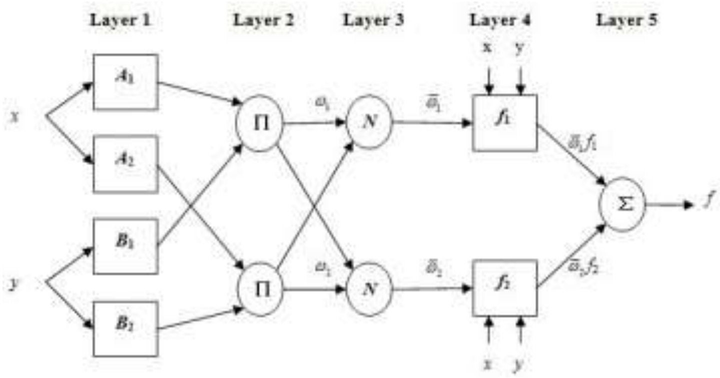


Figure 3 - 12 ANFIS architecture

The different layers of this ANFIS structure are described below:

Layer 1: *input nodes*. Each node of this layer generates membership grades to which they belong to each of the appropriate fuzzy sets using membership functions.

$$O_{1,i} = \mu_{A_i}(x), \quad i = 1,2; \quad O_{1,i} = \mu_{B_{(i-2)}}(y), \quad i = 3,4$$

where $O_{1,i}$ denote the output functions and μ_{A_i} and $\mu_{B_{(i-2)}}$ denote the membership functions. The bell-shaped membership function is used in this study

$$\mu_{A_i} = \frac{1}{1+\left|\frac{x-c_i}{a_i}\right|^{2b_i}} \quad \mu_{B_{(i-2)}} = \frac{1}{1+\left|\frac{y-c_i}{a_i}\right|^{2b_i}}$$

where $\{a_i, b_i, c_i\}$ is the parameter set of the membership functions in the premise part of fuzzy IF/THEN rules that changes the shapes of the membership function. Parameters in this layer are referred to as the premise parameters.

Layer 2: *rule nodes*. In this layer, the AND operator is applied to obtain one output that represents the result of the antecedent for that rule, i.e., firing strength. Firing strength means the degrees to which the antecedent part of a fuzzy rule is satisfied and it shapes the output function for the rule. Hence the outputs $O_{2,i}$ of this layer are the products of the corresponding degrees from layer 1.

$$O_{2,i} = \omega_i = \mu_{Ai}(x)\mu_{Bi}(y), \quad i = 1,2$$

Layer 3: *average nodes*. The main objective of this layer is to calculate the ratio of each rule's firing strength to the sum of all rules' firing strength. Consequently, $\bar{\omega}_i$ is taken as the normalized firing strength.

$$O_{3,i} = \bar{\omega}_i = \frac{\omega_i}{\omega_1 + \omega_2}, \quad i = 1,2$$

Layer 4: *consequent nodes*. The node function of the fourth layer computes the contribution of each rule's toward the total output, and the function is defined as

$$O_{4,i} = \bar{\omega}_i f_i = \bar{\omega}_i \left(p_i + q_i x + r_i y \right), \quad i = 1,2$$

where $\bar{\omega}_i$ is the *i*th node's output from the previous layer, $\{p_i, q_i, r_i\}$ are the coefficients of this linear combination and are also parameter set in the consequent part of the TS fuzzy model.

Layer 5: *output nodes*. The single node computes the overall output by summing all the incoming signals. Accordingly, the defuzzification process transforms each rule's fuzzy results into a crisp output in this layer

$$O_{5,i} = \sum_i \bar{\omega}_i f_i = \frac{\sum_i \omega_i f_i}{\sum_i \omega_i}$$

From the proposed ANFIS structure, it is observed that given the values of premise parameters, the final output can be expressed as a linear combination of the consequent parameters. The output *f* can be written as

$$\begin{aligned} f &= \frac{\omega_1}{\omega_1 + \omega_2} f_1 + \frac{\omega_2}{\omega_1 + \omega_2} f_2 = \bar{\omega}_1 f_1 - \bar{\omega}_2 f_2 \\ &= \left(\bar{\omega}_1\right) p_1 + \left(\bar{\omega}_1 x\right) q_1 + \left(\bar{\omega}_1 y\right) r_1 + \left(\bar{\omega}_2\right) p_2 + \left(\bar{\omega}_2 x\right) q_2 + \left(\bar{\omega}_2 y\right) r_2 \end{aligned}$$

The task of this ANFIS architecture is to tune all the modifiable parameters, including premise parameters ($\{a_i, b_i, c_i\}$) and consequent parameters ($\{p_i, q_i, r_i\}$), to make the ANFIS output match the training data. A hybrid algorithm combining the least squares method and the gradient descent method is adopted to solve this problem. There are two steps in this learning algorithm: in the first step, the least square method is used to identify the consequent parameters, while the antecedent parameters (membership functions) are assumed to be fixed for the current cycle through the training set. Then, the error signals propagate backward. Gradient descent method is used to adjust optimally the premise parameters corresponding to the fuzzy sets in the input domain.

3.5 Conclusion

In our thesis, we have proposed a systematic approach to study the complex relations concerned in sensory evaluation. In this chapter, the theoretical basis of the major computational techniques concerned in the approach has been introduced in detail. According to the specific objectives to be realized in different research phases, the content of this chapter can be summarized as follows. The first step of our approach is to construct an index to measure the classification consistency between different data sets. For this purpose, we introduced the Rough sets theory, then on this basis the rough mereology, and finally the concept of inclusion degree which is the core idea of our approach. During the construction of inclusion degree, we have been aware of the fact that classical data representation based on crisp sets theory cannot be applied to normalize linguistic data as is concerned in our study. In this situation, Fuzzy sets theory was introduced. In this chapter, we presented the definition and basic notions of fuzzy sets, among which is the concept of fuzzy representation, i.e., fuzzy membership function, which has been preferred in our study to represent the sensory data. While the classification consistency is constructed upon the combination of rough sets and fuzzy sets theories, a non-parametric correlation coefficient is employed to examine the ranking consistency between different data sets (the principal of this index will be described in the section where our specific approach is put forward). In order to generate a criterion to measure the general consistency between different data sets in the condition that this criterion should be both robust to noise and easy for interpretation, the concept of fuzzy inference system (FIS) in the background of fuzzy reasoning was introduced. To be specific, the Mamdani's model has been selected to integrate the previous two indices (classification consistency and ranking consistency).

After having constructed the general consistency measure (GCons), we have extended this measure which is originally for single-to-single relations to adapt to multiple-to-single relations. The fuzzy relations, fuzzy logic operations to be involved in this extension have also been introduced in the section of fuzzy sets theory.

Finally, our study has attempted to quantify the multiple-to-single relations defined in previous research phase by establishing multiple inputs and one output predictive models. Given the nature of the sensory data (linguistic, which is uncertain and imprecise to some extent) and the specific problems to be concerned in our study, we propose to develop a neural fuzzy system to solve the modeling problem. And in this chapter, an emphasis has been put on the introduction of the so-called Adaptive network-based fuzzy inference system (ANFIS). It is the most popular neural fuzzy model so far and is also the one we have decided to develop in the current thesis.

CHAPTER 4: Visual interpretability of fabric tactile properties (Experiment I)

In this chapter, we present the first and the fundamental problem of the current thesis, e.g., to what extent tactile properties could be interpreted through visual representations of a given number of textile materials. As the first part of this chapter, a detailed introduction has been given to the sensory experiments of this study, including collection and preparation of experimental samples, generation of descriptive terminology, recruitment of assessing panelists, and practical conduction of sensory evaluations. Then, a mathematical formalization has been done on the sensory data acquired from the experiments. On this basis, in the second part which is also the most significant part of the study, we have proposed a novel approach based on the techniques introduced in the previous chapter (Chapter 3) to study the relations between different sensory data sets. As the third part of this section, our computing method has been applied to the measurement of the consistency of visual to real-touch perceptions of fabric tactile properties. The obtained results have confirmed that most of fabrics' tactile information can be well perceived by assessors through samples' visual representations, while a better performance is detected in video scenarios. Finally, by comparing with the classical correlation method, our approach has been proved to be more efficient since it can lead to stable, clear and interpretable results while being safe to use a small and randomly distributed sample set as is the case in the current study.

4.1 Sensory experiments (Experiment I)

Reliable research data come from standardized experimental preparation and implementation. Sensory evaluations of six flared skirts have been conducted in three scenarios, the real-touch, video, and image scenarios, respectively. The aim of the sensory experiments is to identify the tactile dimensions of the samples in different sensory modalities (e.g., the visual and visual-haptic modalities), so as to investigate the capacity of visual representations to interpret the tactile properties of a given number of textile products.

4.1.1 Experimental samples

4.1.1.1 Collection of sample fabrics

Six textile fabrics with various tactile properties were selected and made into flared skirts as our experimental samples. Some fabric details of these samples are shown in Table 4-1.

Table 4 - 1 Fabric details of the six samples

Sample	Fabric content	Weave structure	Weight (g/m^2)
S1	100% Cotton	Twill	406.6
S2	55% Cotton,45%linen	Plain	201.9
S3	50% Polyester, 50% Acrylic	Plain	120.1
S4	100% Polyester	Twill	108.3
S5	100% Polyester	Twill	224.6
S6	100% Silk	Satin	66.30

All these six skirts are of the same design and production specifications. This is a two-pieces flared skirt, whose waist and length are 68cm and 60cm, respectively. Table 4-2 and Figure 4-1 show the specifications of the flared skirt and the basic pattern of one piece of the skirt, respectively.

Table 4 - 2 Specifications of flared skirt

Specification	cm
Waist	68
Length	60

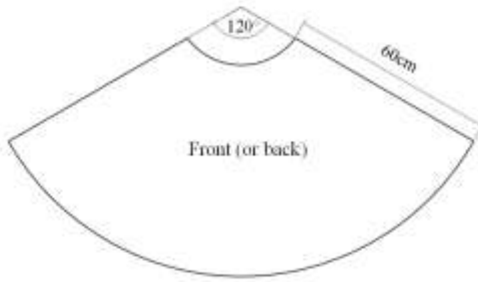


Figure 4 - 1 Two-pieces flared skirt used in the experiment

4.1.1.2 Creation of visual representations

A girl, whose body size is best fit into the sample skirt, was invited as the mannequin in our experiments. Some major specifications of this mannequin are listed in Table 4-3. Two types of visual materials have been created for each sample skirt, respectively, a series of static photos and a dynamic video clip. Training was required before recording.

Table 4 - 3 Major specifications of female mannequin

Height (cm)	Waist (cm)	Hip (cm)
166	65	90

(1) Creation of image representations

In this part, the six skirts were put on the mannequin one after another. A DSLR (Digital single lens reflex) camera whose maximum resolution is 5,616 × 3,744 pixels was used to take photos of each skirt from eight different directions, according to the angle contained between the model's front and the lens, 0° , 45°, 90°, 135°, 180°, 225°, 270° and 315°, respectively.

All the photos were taken in the morning when the daylight is most suitable for shooting (neither too light nor too dim), and in a room which keeps good lighting. In order to avoid color distortion as far as possible, the shooting was done using the available natural light, without flash.

Take sample 1 as an example. Figure 4-2 shows its image representation consisting of eight photos from standardized angles.

(2) Creation of video representations

In this part, the same mannequin was invited to wear these skirts. A camcorder whose maximum resolution is 1920 × 1080 pixels was used to make video clips for all the samples. In each clip, the mannequin was required to walk to-and-fro in front of the camcorder and make postures according to a predesigned standard which is aimed to show comprehensively the dynamic effect of the skirts. Before the real recording, a posture-training session was taken.

In each clip, the model was required to walk to-and-fro and make postures according to a predesigned standard which is aimed to show comprehensively the dynamic effect of the skirts. Before the real recording, a posture-training session was taken. Figure 4-3 shows a screenshot during the video recording of sample 1.

Figure 4 - 2 Image representation of sample 1

Figure 4 - 3 Video representation of sample 1

4.1.2 Panel

In the current study, the sensory evaluations were carried out by a panel of experts with textile background. This panel consisted of 30 female and 12 male members aged between 23 and 55 years. The panelists fall into four classes, university professors (including lecturers, researchers or research assistants from two textile colleges); professionals in textile industry (working mainly on fabric design and fashion design); PhD students and Postgraduate students (working or studying in textile schools), respectively. All these panelists have previously participated in at least twice subjective tests concerning the evaluation of textiles' tactile properties.

During the tests, the sample skirts were evaluated by each panelist in three scenarios, namely, real-touch, video and image scenarios. In order to prevent the possible cross impact between different experimental results, it was decided that each panelist could participate in only one evaluation scenario. The forty-two panelists were randomly put into three groups (fourteen panelists in each group) corresponding to the three different evaluation scenarios. The grouping of the panelists is listed in Table 4-4.

Table 4 - 4 Panelist grouping

Experts in textile domain	Group 1	Group 2	Group 3	In total
	Real-touch scenario	Video scenario	Image scenario	
University professors	4	4	4	12
Professionals in industry	4	4	4	12
PhD student	3	3	3	9
Postgraduate student	3	3	3	9
In total	14	14	14	42

4.1.3 Standardized sensory methods

We use the classical descriptive sensory evaluation method [STONE & SIDEL, 2003] in the following tests. In order to acquire a reliable sensory evaluation, every concerned technique and procedure should be clarified, including the choice of sensory descriptors, evaluation gestures and scales, etc. The aim was to have these techniques or procedures recognized as standard sensory evaluation methods.

The evaluation procedures cover the preliminary work on the choice and definition of each descriptor to be evaluated, the sensory evaluation techniques, time, evaluation scale and evaluation work order. In addition, a well-designed form will help make the evaluation tasks easier to be practiced.

4.1.3.1 Choice of descriptors

To determine the evaluation criteria is crucial for characterizing sensory space. In order to generate a comprehensive tactile description of the samples, a standardized procedure was designed and carried out according to the following steps.

(1) ‘Brainstorming’

A so-called ‘brainstorming’ [OSBORN, 1957, 1963] was launched among some professionals from textile industry to produce an exhaustive list of linguistic descriptors to depict fabric tactile properties from a general point of view. During the discussion, experts were free to speak out words that came to their mind when they thought about the tactile properties of textile products in our daily life. There was no limitation on the form of the words. They can be adjectives, nouns or even verbs. After the discussion, about 220 words were collected.

(2) Screening

In this step, the words that had been collected in the ‘brainstorming’ session were screened for the first time through another discussion among the same panel of experts. During this discussion, experts were asked to remove those words that express hedonic preference like ‘pleasant’, ‘uncomfortable’, etc. The words that would easily lead to confusion in understanding were also removed from the list. Besides, those words that cannot be used to describe the specific samples in our experiment were eliminated as well. Finally, adjective words were determined to be more preferable in the study, and the words in other forms that were regarded as important were turned into adjectives by discussion. After this session, over 50 words remained in the list.

(3) Literature study

Table 4 - 5 Twenty five bipolar descriptors

Nm.	Descriptor pair	Nm.	Descriptor pair
D1	Stiff—pliable	D14	Grainy—non-grainy
D2	Dead—lively	D15	With ridges—without ridges
D3	Draped—non-draped	D16	Bumpy—non-bumpy
D4	Crumply—wrinkle-resistant	D17	Prickly—non-prickly
D5	Non-stretchy—stretchy	D18	Fuzzy—non-fuzzy
D6	Loose—tight	D19	Non-slippery—slippery
D7	Flimsy—firm	D20	Harsh—soft
D8	Thin—thick	D21	Warm—cool
D9	Light—heavy	D22	Cotton-like
D10	Soft—hard(in compression)	D23	Silk-like
D11	Non-springy—springy	D24	Linen-like
D12	Non-full—full	D25	Synthetic-like
D13	Rough—smooth(overall feeling)		

A final screening of the descriptive words was done on the basis of the information gathered from the literature [CIVILLE, 1990]; [*AATCC Technical Manual*, 2007]. Among the over 50 words obtained from the previous session, those words that were delivered in a less normalized way were removed or replaced by the ones from the literature. For example, the descriptor 'weak' was replaced by 'flimsy'.

Finally, twenty five pairs of descriptors were determined as the tactile evaluation criteria in our study which are listed in Table 4-5.

For a better understanding, these tactile descriptors have been classified by experts, according to the fabric properties they are supposed to express, into four major categories, mechanical, surface, basic, and material recognition, respectively. What's worth mentioning is that due to the nature of human language, one descriptor can cover several property aspects, and thus there are overlaps between different categories. The classification (and sub-classification if any) of the selected twenty two descriptors is shown in Table 4-6.

Table 4 - 6 Classification of tactile descriptors

Category	Mechanical			Surface	Basic	Material recognition
	Bending	Tensile and shearing	Compression			
Tactile descriptors	D1, D2, D3, D4	D2, D3, D4, D5, D6, D7	D10, D11,D12	D13 ~D21	D6, D7, D8, D9	D22~D25

For each descriptor pair, a detailed explanation to both its definition and the corresponding assessing gestures was determined by referring to the literatures [BISHOP, 1996]; [MEILGAARD, 1991] and especially, by carrying out a discussion among the experts (Table 4-7 (a) and (b)). Initial tests were performed to decide whether the evaluation techniques were understood and could easily be applied by the panelists.

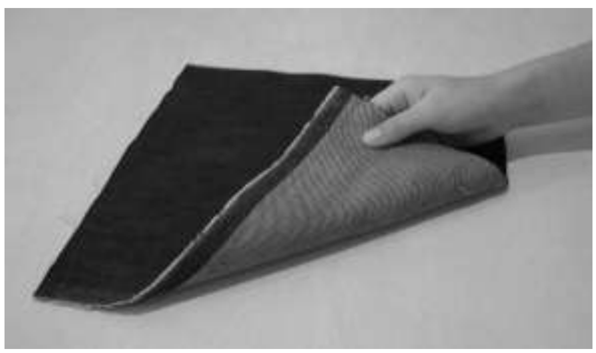


Figure 4 - 4 Gesture for “Stiff-Pliable”

Figure 4 - 5 Gesture for “Rough-Smooth”

Table 4 - 7 (a) Definitions and gestures of fabric tactile descriptors (from D1 to D10)

D1	Stiff—pliable
	Definition and gestures: A textile that is stiff is not easily bent, rigid and inflexible. A textile that is pliable is soft and easily bent, flexed or twisted, which is the opposite feeling of "stiff". To assess this attribute, the panelist holds the fabric between the thumb and the other four fingers of his/her most used hand; while moving the fabric back and forth, he/she assesses the resistance (shown in Figure 4-4).
D2	Dead—lively
	Definition and gestures: A textile that is lively is flexible and quickly resilient (after some bending deformation (for example grasping)). To assess this attribute, the panelist tries to grasp the fabric and keep it in the hand for a short while and then free the hand to feel the fabric's recovering strength and speed.
D3	Draped—non-draped
	Definition and gestures: The behavior of the fabric to drape. To get the sample between the thumb and index finger so that it "drapes" down across the knuckles. The closer it follows the line of the knuckles, the more draped it is.
D4	Crumply—wrinkle-resistant
	Definition and gestures: A textile that is crumply wrinkles easily; A textile that is wrinkle-resistant is not likely to have wrinkles after it is grasped, folded or pressed.
D5	Non-stretchy—stretchy
	Definition and gestures: A textile that is stretchy is capable of being easily stretched and resuming former size and shape.
D6	Loose—tight
	Definition and gestures: A textile that is tight is closely weaved; A textile that is loose is not tight or dense in structure.
D7	Flimsy—firm
	Definition and gestures: A textile that is flimsy is thin and weak, and is destroyed easily; A textile that is firm has a compact weave density and is not soft or yielding to pressure.
D8	Thin—thick
	Definition and gestures: A textile that is thick is of big extent from one surface to the opposite. 'Thin' is opposite to 'thick'.
D9	Light—heavy
	Definition and gestures: A textile that is heavy is of big physical weight. 'Light' is opposite to 'heavy'.
D10	Soft—hard(in compression)
	Definition and gestures: A textile that is hard is resistant to pressure. 'Soft (in compression)' is opposite to 'hard'.

Table 4-7 (b) Definitions and gestures of fabric tactile descriptors (from D11 to D21)

D11	Non-springy—springy
	Definition and gestures: A textile that is firm has a compact weave density and is not soft or yielding to pressure.
D12	Non-full—full
	Definition and gestures: Fullness is a feeling coming from a combination of bulky, rich, and well-formed impression. A fabric with a springy property in compression and thickness, accompanied by a warm feeling gives a high value.
D13	Rough—smooth(overall feeling)
	Definition and gestures: An overall surface judgment. A textile with smooth surface is free from roughness, e.g. bumps, ridges or irregularities, etc. when it is touched by hand. To assess this attribute, the panelist moves the fingers of his/her most used hand on the fabric surface freely and tries to feel the unevenness. The more uneven the surface is, the more rough the fabric is, and the less smooth it is.(as is shown in Figure 4-5)
D14	Grainy—non-grainy
	Definition: A textile that is grainy has a rough texture as if it is covered with small particles on the surface.
D15	With ridges—without ridges
	Definition: Ridges: Long narrow raised strips or elevations on the surface.
D16	Bumpy—non-bumpy
	Definition: A textile that is bumpy has an uneven surface.
D17	Prickly—non-prickly
	Definition: A textile that is prickly is covered with prickles on the surface, which is not smooth, soft or pleasant to touch.
D18	Fuzzy—non-fuzzy
	Definition: If a textile is fuzzy or downy, it has a covering with fine light hairs (fuzz), which feels soft and like fur.
D19	Non-slippery—slippery
	Definition: A surface texture concerning the fabric friction. A textile that is slippery tends to slip or slide when it is put on the surface of another same textile.
D20	Harsh—soft
	Definition: A textile that is soft on the surface has a mixed feeling which is very smooth, fine and pleasant to touch.
D21	Warm—cool
	Definition: A textile that is warm on the surface has the quality of being at a comfortable and agreeable degree of heat when it is touched by skin.

4.1.3.2 Evaluation scales

An 11-point scale degreed from 0 to 10 was applied for the evaluation. In order to prevent miss-scoring, every point on the scale was well defined semantically, as is shown in Table 4-8. For example, if a sample was considered to be very stiff, then its value on the 'stiff-pliable' should be 1, so on and so forth.

Table 4 - 8 Evaluation scale and semantic explanation

0	1	2	3	4	5	6	7	8	9	10
Extremely	Very	Quite	Fairly	More than medium	Medium	More than medium	Fairly	Quite	Very	Extremely

4.1.3.3 Training

In sensory evaluations of fabric tactile properties, the panelists may make assessment by only seeing, only touching or both seeing and touching the fabric. With respect to the current study, it was decided that, in the real-touch scenario, the panelists could both see and touch the fabric, which is in accordance with our real life experience.

Before the conduction of real tests, all the forty two panelists were given a six-hour instruction on the major purpose of the current sensory tests and all the evaluation techniques. For the panelists in different test scenarios, an instruction about the concerned evaluation procedures was made separately for them.

A training session was organized for the panelists in all the three scenarios. This is a real-touch training, the aim of which is to strengthen the panelists' evaluation-related knowledge. For the panelists in the visual scenarios, this session is as significant as it is for those in the real-touch scenario, because when they are put into a non-haptic experience, a strong awareness of the real evaluation techniques in their mind would help them recall the associated memory in a more quick and correct way.

In this training session, some training samples (different from the six experimental samples) were used to help the panelists get familiar with all the descriptors, gestures as well as the evaluation scales. This session took about 6 hours.

4.1.4 Experiments

4.1.4.1 Real-touch scenarios

Fourteen panelists took part in the real-touch scenario. Before the tests, all the samples were conditioned for a minimum of 24 hours under the standard atmospheric condition (20±2 C temperature, 65±2% relative humidity). And the entire experiment was done in a laboratory satisfying this condition. During the tests, the six samples were laid on a big table at a time, and the panelists were suggested to finish the scoring of all the samples on one descriptor, and then go on with the next. The evaluation should be carried out individually for each panelist. As shown in Figure 4-6 (a), the panelist is attending the real-touch scenario.

Before getting started, the panelist would be asked to wash and dry his/her hands with the non-moisturizing soap and paper towel provided. The panelist might start the evaluation when he/she was ready.

(a)Real-touch

(b) Video

(c) Image

Figure 4 - 6 Different sensory scenarios

4.1.4.2 Video scenarios

Another fourteen panelists participated in the video evaluation scenario, where the video clips of the experimental samples were shown at a time on several computer screens, whose displaying parameters were adjusted to be strictly the same with each other. The panelists were also required to conduct the tests individually. And during the process, they were free to control the playback of the video clips and make pauses wherever they needed. As shown in Figure 4-6 (b), the panelist is attending the video scenario.

4.1.4.3 Image scenarios

The left fourteen panelists took part in this scenario, in which the images of the six samples were shown at a time on several computer screens, whose displaying parameters were adjusted to be strictly the same with each other. The tests were carried out individually for each panelist. And during the process, the panelists were free to control the display of the images by either changing the displaying order or zooming in / out the photo. As shown in Figure 4-6 (c), the panelist is attending the image scenario.

4.1.4.4 Mathematical formalization

After the above experiments, we have obtained, for each evaluation scenario, a matrix of aggregated sensory data, in which any element represents, for a specific sample (denoted in columns), the average evaluation value on the corresponding descriptor or attribute (denoted in rows) through all the panelists. To be specific, for the real-touch, video and image scenarios, the corresponding data matrices are formalized as T, V, and O respectively as below.

$$T=\begin{bmatrix} t_1(e_1) & t_2(e_1) & \cdots & t_n(e_1) \\ t_1(e_2) & t_2(e_2) & \cdots & t_n(e_2) \\ \vdots & \vdots & \ddots & \vdots \\ t_1(e_m) & t_2(e_m) & \cdots & t_n(e_m) \end{bmatrix},\ V=\begin{bmatrix} v_1(e_1) & v_2(e_1) & \cdots & v_n(e_1) \\ v_1(e_2) & v_2(e_2) & \cdots & v_n(e_2) \\ \vdots & \vdots & \ddots & \vdots \\ v_1(e_m) & v_2(e_m) & \cdots & v_n(e_m) \end{bmatrix},\ O=\begin{bmatrix} o_1(e_1) & o_2(e_1) & \cdots & o_n(e_1) \\ o_1(e_2) & o_2(e_2) & \cdots & o_n(e_2) \\ \vdots & \vdots & \ddots & \vdots \\ o_1(e_m) & o_2(e_m) & \cdots & o_n(e_m) \end{bmatrix}$$

in which, $U = \{e_1, e_2, \ldots, e_m\}$ is the set of samples, and m and n the numbers of samples and sensory descriptors respectively. In our study, $m= 6$, $n=25$ and $t_j(e_i)$, $v_j(e_i)$, and $o_j(e_i)$ are the averaged evaluation scores (real numbers) varying between 0 and 10. ($i\in\{1, 2, \ldots, 6\}$ and $j\in\{1, 2, \ldots, 25\}$).

In the following section, we will model the relations between tactile and visual perceptions of the samples from these sensory data.

4.2 Study of relations between sensory data sets

In our study, in order to measure the degree to which the tactile properties of a textile product could be interpreted through its visual representations, a novel approach is proposed on the basis of the so-called fuzzy inclusion defined according to rough set theory and fuzzy techniques.

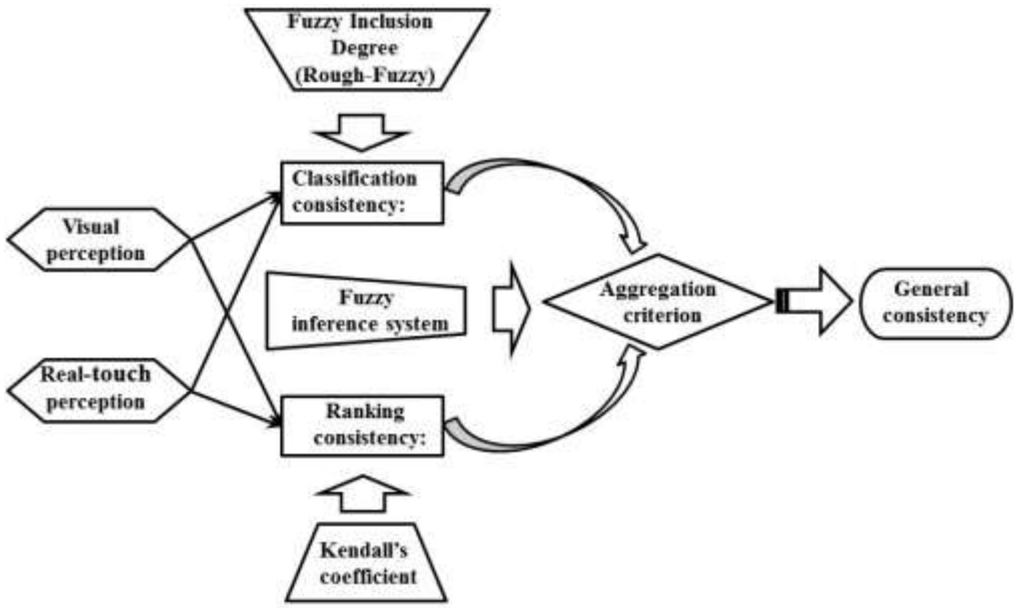


Figure 4 - 7 General framework for our approach

To be specific, this approach is constructed upon two indices, the Classification Consistency (*FCons*) based on the concept of fuzzy inclusion degree, and the Ranking Consistency (*RCons*) obtained from the non-parametric ranking coefficient (Kendall's tau), respectively. The general framework of our approach is illustrated in Figure 4-7. Correspondingly, the following discussion is carried out in two parts. First, Section 4.2.1 illustrates the principles and formalization of the major index *FCons*. Then Section 4.2.2 describes the principles and formalization of another important index *RCons*, and Section 4.2.3 is about the development of a fuzzy inference system in order to generate the General Consistency (*GCons*) as a fusion measure of the previous two indices.

4.2.1 Fuzzy classification consistency

4.2.1.1 Problematic

The topic of this part is to measure the classification consistency (*FCons*) of visual (image, or video) perceptions of fabrics' tactile properties to real-touch ones. The formalization of the present problem is given below. Let $U = \{e_1, e_2, \ldots, e_m\}$ (in our case, $m= 6$) be the set of samples. The corresponding evaluation scores have been obtained from the visual (either image or video) and real-touch perceptions on all the samples as are formalized previously (in Section 4.1.4.4). But in order to better adopt the mathematical approach to be proposed in this section, for any specific pair of tactile descriptors such as 'Stiff—Pliable', the aggregated visual and real-touch data sets are denoted as $C = (c(e_1) \ \ldots \ c(e_m))^T$ and $D = (d(e_1) \ \ldots \ d(e_m))^T$ ($m= 6$), respectively. All the evaluation scores $c(e_i)$'*s* and $d(e_i)$'*s* are real numbers varying between 0 and 10. In the following discussion, the visual perception C is taken as condition variable and the real-touch perception D as decision variable. According to rough sets philosophy, the knowledge acquisition is in fact a process of knowledge classification. Different knowledge would generate different partitions of data. From the previous two vectors of C and D, we obtain two partitions for the visual and real-touch results, i.e. $U / C = \{X_0, X_1, \ldots, X_q\}$ and $U / D = \{Y_0, Y_1, \ldots, Y_q\}$ (in our case, $q= 10$). $X_i \in U/C\left(i=0,1,\cdots,10\right)$ (or $Y_j \in U/D\left(j=0,1,\cdots,10\right)$) is the class of samples in which the evaluation scores are all i (or all j). In practice, some X_i (or Y_j) can be empty if its index i (or j) does not exist in the evaluation scores of all the samples e_k's.

Thus, the aim of this part of the approach is to compute the extent to which the partition of the condition set (visual perception) is consistent with that of the decision set (real-touch perception).

4.2.1.2 Inclusion degree

As illustrated in Chapter 3, inclusion degree is a concept originated from rough mereology and is aimed to measure to what extent the classification of the condition set is in consistent with that of the decision set.

Taking a tactile attribute 'stiff—pliable' as an example (Figure 4-8), different sensory scenarios will generate different perceptions which develop different knowledge classification. If we consider the visual perception as the condition set, the real-touch perception as decision set, our aim to compute the inclusion degree between the two sensory modalities is in fact, according to the theory [PAWLAK, 1982], to investigate the percentage of correct classification in between.

Given the current problem, let $S=(U,C\bigcup D)$ be a complete decision table, U the collection of experimental samples, $X\in U/C$ an equivalence class representing the visual perceptions of the samples on a specific tactile property and $U/D=\{[e]_D : e\in U\}$ representing the corresponding real-touch perceptions of the samples. For any sample $e_k\in U$, the inclusion degree of X_i with respect to $[e_j]_D$ is denoted by:

$$Inc([e_k]_D/X_i)=\frac{|X_i\bigcap[e_k]_D|}{|X_i|},\ (i=0,1,\cdots,10\ ;k=1,2,\cdots,6) \tag{4-1}$$

where $0\le Inc([e_k]_D/X_i)\le 1$.

$[e_k]_D$ is the set of samples that are classified into the same group with e_k according to the decision attribute.

It is evident that, if $Inc([e_k]_D/X_i)=1$, then X_i can be said to be consistent with respect to $[e_k]_D$, or one has $X_i\subseteq[e_k]_D$ (which is called a complete inclusion).

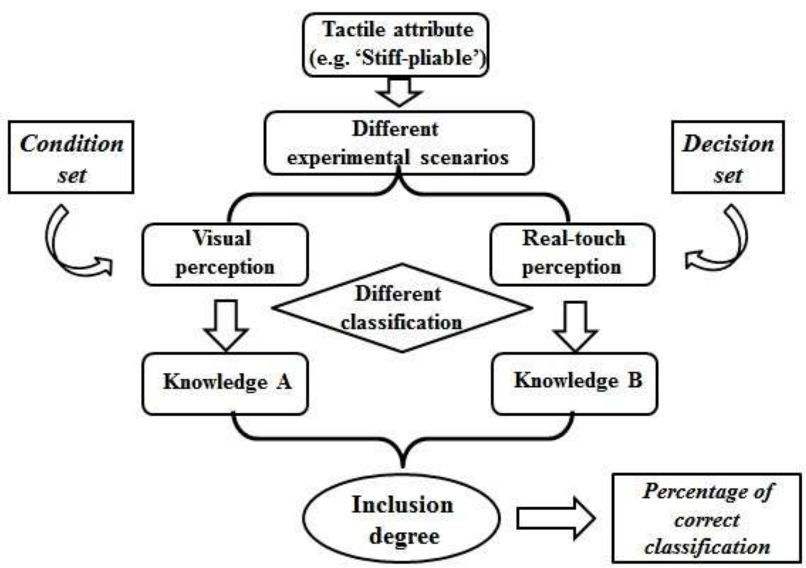


Figure 4 - 8 Illustration of inclusion degree on 'stiff—pliable'

4.2.1.3 Consistency degree

According to rough sets theory, based on the above inclusion degree, we can define the classification consistency (*Cons*) of the visual perception to real-touch for any fabric tactile property. Mathematically, it expresses the percentage of objects which can be correctly classified to decision classes of U/D by the condition attribute set C.

Let $S=(U,C\cup D)$ be a complete decision table, $U=\{e_1,e_2,\cdots,e_m\}(m=6)$ the set of samples, $U/C=\{X_0,X_1,\cdots,X_q\}(q=10)$ and $U/D=\{[e]_D:e\in U\}$ the equivalence classes of the condition attribute and the decision attribute respectively. Notably, the aim of the current study is to analyse, under different experimental conditions, the panellists' perceptual difference on the same fabric tactile property. In consequence, the condition attribute is determined as the same with the decision attribute. Here, a consistency measure of an equivalence class X_i of the condition part U/C with respect to the decision part U/D is defined as:

$$Cons(X_i,D)=1-\frac{4}{|U|}\sum_{k=1}^{|U|}Inc([e_k]_D/X_i)(1-Inc([e_k]_D/X_i)),\quad (i=0,1,\cdots,10\ ;k=1,2,\cdots,6) \tag{4-2}$$

where $0\le Cons(X_i,D)\le 1$, $Inc([e_k]_D/X_i)$ is the inclusion degree of X_i into $[e_k]_D$ for sample e_k.

Then, on the above basis, the classification consistency measure (*Cons*) of *C* with respect to *D* is defined as

$$Cons(C,D)=\sum_{i=0}^{q}\frac{|X_i|}{|U|}\left(1-\frac{4}{|U|}\sum_{k=1}^{|U|}Inc([e_k]_D/X_i)(1-Inc([e_k]_D/X_i))\right),\ (k=1,2,\cdots,6;\ q=10) \tag{4-3}$$

where $Inc([e_k]_D/X_i)$ is the inclusion degree of X_i into $[e_k]_D$ for sample e_k.

4.2.1.4 Fuzzy classification consistency

However, rough set theory assumes that information systems contain only crisp data and any feature (attribute) of any object (example) has a precise and unique value. However, real-world data are generally imprecise, which is especially the case for the linguistic observations concerned in sensory problems. An inclusion degree based on the previous crisp partitions of samples according to which any sample is sharply discriminated as either member or non-member of an equivalence class, might lead to serious information loss. For a sample e_k not belonging to a class X_i, its adhesion to this equivalence class is consequently taken as null. For any specific equivalence class, it does not make any difference between samples close to it and those far from it.

But in the current sensory study, the definition of each variable (i.e. tactile property) is imprecise as well as the significance of the corresponding equivalence classes. Taking the descriptor pair "Stiff- pliable" as an example, the semantic scale of "quite stiff" is represented by the equivalence class X_2. Obviously, the two-valued characteristic function used in crisp sets is no longer capable of describing this vague concept since the corresponding equivalence class has imprecise boundaries. Therefore, it is meaningful to associate a *grade* with any sample to quantify its degree of adhesion to X_2 so that the samples closer to this class are considered to go better with the concept "quite stiff" than those far from it.

(1) Fuzzy inclusion degree

As introduced in Chapter 3, the notion of degrees of adhesion or partial membership is the main idea in fuzzy set theory and in fuzzy logics, according to which we have modified the previous inclusion degree using the concept of fuzzy partition. [DUBOIS, 1996]

For any sample $e_k \in U$, the modified inclusion degree $FInc\left(\left[e_k\right]_D / X_i\right)$ is illustrated as:

$$FInc\left(\left[e_k\right]_D / X_i\right) = \sum_{l=1}^{m} \min\left(\mu_{X_i}(e_l), \mu_{[e_k]_D}(e_l)\right) / \sum_{l=1}^{m} \mu_{X_i}(e_l), (m=6) \tag{4-4}$$

in which, X_i denotes the ith condition set and $\left[e_k\right]_D \subset U/D = \left\{Y_0, Y_1, \cdots, Y_q\right\}$ is the decision set where the sample e_k belongs. Here, e_k are considered to belong to $\left[e_k\right]_D$, when the following holds.

$$\mu_{[e_k]_D}(e_k) = \max\left\{\mu_{Y_0}(e_k), \mu_{Y_1}(e_k), \cdots, \mu_{Y_q}(e_k)\right\}, (q=10) \tag{4-5}$$

The classes X_i's and Y_j's constitute two fuzzy partitions (sets) for the attributes C and D and they are characterized by the fuzzy membership functions $\mu_{X_i}(e)$ and $\mu_{Y_j}(e)$, defined as:

$$\mu_{X_i}(e) = 1 - h\left|i - c(e)\right| \tag{4-6}$$

$$\mu_{Y_j}(e) = 1 - h\left|j - d(e)\right| \tag{4-7}$$

They are triangular functions centered on i and j respectively. h is the coefficient controlling the sensitivity of these functions. $c(e)$ and $d(e)$ are evaluation scores of the sample e for the attributes C and D. In the current study, we assign 0.2 to h as a general case.

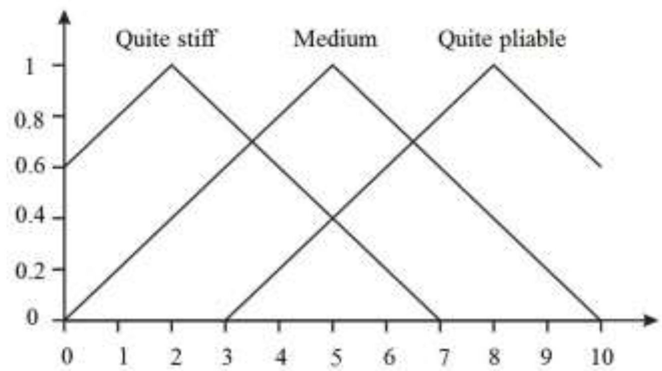


Figure 4 - 9 Membership functions of "stiff— pliable"

Notably, 1) the decision set where a sample e_k might belong is determined according to the maximum membership principle, i.e., e_k is believed to belong to a decision set Y_j when the corresponding fuzzy membership degree $\mu_{Y_j}(e_k)$ reaches the highest among all the decision sets; 2) given the present problem, any $\mu_{X_i}(e)$ or $\mu_{Y_j}(e)$ whose value is negative would be taken as zero for further computing. Figure 4-9 depicts the membership function of the descriptor pair "stiff—pliable" as an example.

(2) Modified classification consistency (*FCons*)

On the above basis, the classification consistency of X_i with respect to D has been modified as:

$$FCons(X_i, D) = 1 - \frac{4}{\sum_{i=0}^{q}\sum_{k=1}^{m}\mu_{X_i}(e_k)}\sum_{k=1}^{m} FInc\left([e_k]_D / X_i\right)\left(1 - FInc\left([e_k]_D / X_i\right)\right)\ (m=6) \tag{4-8}$$

where, $FInc\left([e_k]_D / X_i\right)$ is the fuzzy inclusion degree of X_i into $[e_k]_D$ for sample e_k. Similar to the consistency degree defined in Eq. (4-2), we have $0 < FCons(X_i, D) < 1$. This is due to the following facts: i) for each sample e_k, there always exists a Y_j whose value j is the closest to $d(e_k)$ (the difference is smaller than 0.5), i.e. $\mu_{Y_j}(e_k) \geq 0.9$; ii) $0 \leq FInc\left([e_k]_D / X_i\right)\left(1 - FInc\left([e_k]_D / X_i\right)\right) \leq \frac{1}{4}$ holds for any X_i and Y_j.

Hitherto, the final classification consistency of the condition attribute C with respect to the decision attribute D can be constituted as:

$$FCons(C,D)=\sum_{i=0}^{q}\frac{\sum_{k=1}^{m}\mu_{X_i}(e_k)}{\sum_{i=0}^{q}\sum_{k=1}^{m}\mu_{X_i}(e_k)}FCons(X_i,D),\left(m{=}6,\ q{=}10\right) \tag{4-9}$$

where, $FInc\left(\left[e_k\right]_D/X_i\right)$ is the fuzzy inclusion degree of X_i into $[e_k]_D$ for sample e_k.

(3) An illustrative example

Table 4-9 shows a complete decision table of the descriptor pair 'Stiff-- pliable' (D1), where C is the condition set representing either the evaluation values obtained in video or image scenarios, while D is the decision set referring to the values obtained in real-touch scenarios.

Table 4 - 9 Decision table of 'Stiff—pliable' (D1)

Sample	C (Video)		D (Real-touch)
	Video	Image	
S1	2.786	3.000	2.643
S2	4.071	6.500	4.357
S3	1.857	5.833	1.429
S4	8.071	1.000	8.429
S5	7.286	5.167	6.214
S6	8.786	8.833	9.214

As an illustrative example, we consider the fuzzy classification consistency of the video evaluations to the real-touch ones of the six samples on D1.

For sample 1, its fuzzy membership values with respect to each conditional equivalence class X_i and each decisional equivalence class Y_j are computed as follows.

$\mu_{X_0}\left(e_1\right)=1-0.2\left|0-2.786\right|=0.443$,

$\mu_{X_1}\left(e_1\right)=0.643$, $\mu_{X_2}\left(e_1\right)=0.843$, $\mu_{X_3}\left(e_1\right)=0.957$, $\mu_{X_4}\left(e_1\right)=0.757$, $\mu_{X_5}\left(e_1\right)=0.557$, $\mu_{X_6}\left(e_1\right)=0.357$, $\mu_{X_7}\left(e_1\right)=0.157$, $\mu_{X_8}\left(e_1\right)=\mu_{X_9}\left(e_1\right)=\mu_{X_{10}}\left(e_1\right)=0$.

$\mu_{Y_0}\left(e_1\right)=1-0.2\left|0-2.643\right|=0.471$,

$\mu_{Y_1}\left(e_1\right)=0.671$, $\mu_{Y_2}\left(e_1\right)=0.871$, $\mu_{Y_3}\left(e_1\right)=0.929$, $\mu_{Y_4}\left(e_1\right)=0.729$, $\mu_{Y_5}\left(e_1\right)=0.529$, $\mu_{Y_6}\left(e_1\right)=0.329$, $\mu_{Y_7}\left(e_1\right)=0.129$, $\mu_{Y_8}\left(e_1\right)=\mu_{Y_9}\left(e_1\right)=\mu_{Y_{10}}\left(e_1\right)=0$.

In this manner, the fuzzy membership values of all the six samples with respect to X_i and Y_j are obtained and listed in Table 4-10 and Table 4-11.

Table 4 - 10 Fuzzy membership values with respect to Xi

Sample	$\mu_{X_0}(e_l)$	$\mu_{X_1}(e_l)$	$\mu_{X_2}(e_l)$	$\mu_{X_3}(e_l)$	$\mu_{X_4}(e_l)$	$\mu_{X_5}(e_l)$
S1	0.443	0.643	0.843	0.957	0.757	0.557
S2	0.186	0.386	0.586	0.786	0.986	0.814
S3	0.629	0.829	0.971	0.771	0.571	0.371
S4	0.000	0.000	0.000	0.000	0.186	0.386
S5	0.000	0.000	0.000	0.143	0.343	0.543
S6	0.000	0.000	0.000	0.000	0.043	0.243
Sample	$\mu_{X_6}(e_l)$	$\mu_{X_7}(e_l)$	$\mu_{X_8}(e_l)$	$\mu_{X_9}(e_l)$	$\mu_{X_{10}}(e_l)$	
S1	0.357	0.157	0.000	0.000	0.000	
S2	0.614	0.414	0.214	0.014	0.000	
S3	0.171	0.000	0.000	0.000	0.000	
S4	0.586	0.786	0.986	0.814	0.614	
S5	0.743	0.943	0.857	0.657	0.457	
S6	0.443	0.643	0.843	0.957	0.757	

Table 4 - 11 Fuzzy membership values with respect to Y_j

Sample	$\mu_{Y_0}(e_l)$	$\mu_{Y_1}(e_l)$	$\mu_{Y_2}(e_l)$	$\mu_{Y_3}(e_l)$	$\mu_{Y_4}(e_l)$	$\mu_{Y_5}(e_l)$
S1	0.471	0.671	0.871	0.929	0.729	0.529
S2	0.129	0.329	0.529	0.729	0.929	0.871
S3	0.714	0.914	0.886	0.686	0.486	0.286
S4	0.000	0.000	0.000	0.000	0.114	0.314
S5	0.000	0.000	0.157	0.357	0.557	0.757
S6	0.000	0.000	0.000	0.000	0.000	0.157
Sample	$\mu_{Y_6}(e_l)$	$\mu_{Y_7}(e_l)$	$\mu_{Y_8}(e_l)$	$\mu_{Y_9}(e_l)$	$\mu_{Y_{10}}(e_l)$	
S1	0.329	0.129	0.000	0.000	0.000	

S2	0.671	0.471	0.271	0.071	0.000	
S3	0.086	0.000	0.000	0.000	0.000	
S4	0.514	0.714	0.914	0.886	0.686	
S5	0.957	0.843	0.643	0.443	0.243	
S6	0.357	0.557	0.757	0.957	0.843	

Next, the fuzzy inclusion degree of X_i with respect to $\left[e_j\right]_D$ is obtained as bellow.

Take sample 1 as an example,

$$FInc\left(\left[e_1\right]_D / X_0\right) = \sum_{l=1}^{6} \min\left(\mu_{X_0}(e_l), \mu_{Y_3}(e_l)\right) / \sum_{l=1}^{6} \mu_{X_0}(e_l)$$
$$= \left(\begin{array}{l} \min(0.443, 0.929) + \min(0.186, 0.729) + \min(0.629, 0.686) + \\ \min(0,0) + \min(0, 0.357) + \min(0,0) \end{array}\right) \Big/ (0.443 + 0.186 + 0.629 + 0 + 0 + 0)$$
$$= 1$$

Then, $FInc\left(\left[e_1\right]_D / X_1\right) = 0.923$, $FInc\left(\left[e_1\right]_D / X_2\right) = 0.881$, $FInc\left(\left[e_1\right]_D / X_3\right) = 0.935$, $FInc\left(\left[e_1\right]_D / X_4\right) = 0.832$, $FInc\left(\left[e_1\right]_D / X_5\right) = 0.691$, $FInc\left(\left[e_1\right]_D / X_6\right) = 0.515$, $FInc\left(\left[e_1\right]_D / X_7\right) 0.316$, $FInc\left(\left[e_1\right]_D / X_8\right) = 0.197$, $FInc\left(\left[e_1\right]_D / X_9\right) = 0.152$, $FInc\left(\left[e_1\right]_D / X_{10}\right) = 0.195$.

Table 4 - 12 Fuzzy inclusion degrees for each sample

Sample	$FInc\left(\left[e_l\right]_D / X_0\right)$	$FInc\left(\left[e_l\right]_D / X_1\right)$	$FInc\left(\left[e_l\right]_D / X_2\right)$	$FInc\left(\left[e_l\right]_D / X_3\right)$
S1	1.000	0.923	0.881	0.935
S2	0.886	0.815	0.750	0.806
S3	1.000	0.969	0.798	0.667
S4	0.148	0.146	0.113	0.156
S5	0.477	0.431	0.417	0.462
S6	0.057	0.038	0.030	0.081
Sample	$FInc\left(\left[e_l\right]_D / X_4\right)$	$FInc\left(\left[e_l\right]_D / X_5\right)$	$FInc\left(\left[e_l\right]_D / X_6\right)$	$FInc\left(\left[e_l\right]_D / X_7\right)$
S1	0.832	0.691	0.515	0.316
S2	0.901	0.824	0.623	0.422
S3	0.545	0.431	0.294	0.165
S4	0.292	0.495	0.667	0.796

S5	0.574	0.775	0.907	0.811
S6	0.223	0.392	0.529	0.660
Sample	$FInc\left([e_l]_D / X_8\right)$	$FInc\left([e_l]_D / X_9\right)$	$FInc\left([e_l]_D / X_{10}\right)$	
S1	0.197	0.152	0.195	
S2	0.305	0.281	0.313	
S3	0.074	0.006	0.000	
S4	0.872	0.912	1.000	
S5	0.670	0.632	0.727	
S6	0.773	0.912	0.992	

The fuzzy inclusion degrees of the other five samples can be obtained in the same manner as are shown in Table 4-12.

On this basis, the classification consistency of X_i with respect to D is computed as follows.

$$FCons(X_0, D) = 1 - \frac{4}{\sum_{i=0}^{10}\sum_{k=1}^{6}\mu_{X_i}(e_1)}\sum_{k=1}^{6} FInc\left([e_1]_D / X_i\right)(1 - FInc\left([e_1]_D / X_i\right))$$
$$= 1 - \frac{4}{27}\left(0 + 0.101 + 0 + 0.126 + 0.249 + 0.054\right)$$
$$= 0.922$$

Similarly, we obtain, $FCons(X_1, D) = 0.902$, $FCons(X_2, D) = 0.878$, $FCons(X_3, D) = 0.868$, $FCons(X_4, D) = 0.837$, $FCons(X_5, D) = 0.812$, $FCons(X_6, D) = 0.815$, $FCons(X_7, D) = 0.831$, $FCons(X_8, D) = 0.860$, $FCons(X_9, D) = 0.892$, $FCons(X_{10}, D) = 0.914$.

Finally, for the descriptor pair 'Stiff--pliable' (D1), the classification consistency of the video perception with respect to the real-touch perception can be obtained as,

$$FCons(C, D) = \sum_{i=0}^{10}\frac{\sum_{k=1}^{6}\mu_{X_i}(e_k)}{\sum_{i=0}^{10}\sum_{k=1}^{6}\mu_{X_i}(e_k)} FCons(X_i, D)$$
$$= \frac{1.257}{27}\times 0.902 + \frac{1.857}{27}\times 0.878 + \frac{2.400}{27}\times 0.868 + \frac{2.657}{27}\times 0.837 +$$
$$\frac{2.886}{27}\times 0.812 + \frac{2.914}{27}\times 0.815 + \frac{2.914}{27}\times 0.831 + \frac{2.943}{27}\times 0.860 +$$
$$\frac{2.900}{27}\times 0.892 + \frac{2.443}{27}\times 0.902 + \frac{1.829}{27}\times 0.914$$
$$= 0.859.$$

In the same manner, we obtained the fuzzy classification consistency of the image evaluations to the real-touch ones on the descriptor pair 'stiff—pliable' as 0.798. Obviously, the image results are inferior to the video ones. Since the significance of *FCons* is to measure to what extent the classification criteria of one dataset accord with those of the reference dataset. The above computing results reveal that, the skirts' video displays, as compared with the image ones, can better evoke the panelists' potentials to as correctly (or in other words, close to real conditions) as possible classify the samples according to their stiffness.

4.2.2 Ranking consistency

According to the above illustration, the classification consistency measure $FCons(C, D)$ quantifies the extent to which the classification of the condition set (or, the visual result set) is consistent with that of the decision set (or, the real-touch result set). However, the ordinal consistency between the sets is not well taken into consideration. For example, according to the idea of inclusion degree, the two classifications, {(1 2 3) (4 5)} and {(3 2 1) (5 4)}, may have no difference, since according to the available classificatory criteria, the inclusion relations of each element in these two sets are regarded as identical. But actually, in an information system, the element's different positions in the two sets may lead to big differences between the knowledge to be represented respectively. Therefore, it is meaningful to involve another index to measure the ordinal differences between the data obtained from different sensory modalities, which would work as a supplement to the classification consistency measure (*FCons*). For this purpose, Kendall's rank coefficient is employed in our study [SIEGEL, 1977] as a rank consistency measure (*RCons*).

As a non-parametric measure of rank correlation, Kendall's tau τ depends upon the number of inversions of pairs of objects which would be needed to transform one rank order into the other. For the sample set $U = \{e_1,\ e_2,\ e_3,\ e_4,\ e_5,\ e_6,\}$, $C = (c(e_1)\ \ldots\ c(e_6))^T$ and $D = (d(e_1)\ \ldots\ d(e_6))^T$ are observations corresponding to the visual evaluation (i.e. for the video or image scenarios) and the real-touch evaluation (i.e. for the real scenario), respectively. Kendall's rank correlation coefficient τ or *RCons(C, D)* is computed from:

$$RCons(C,D)=\tau(C,D)=1-\frac{2d_{\Delta}(C,D)}{n(n-1)} \quad (4\text{-}10)$$
$$-1\leq\tau(C,D)\leq 1$$

Where n is the number of samples. $d_{\Delta}(C,D)$ denotes the symmetric difference between two attribute sets C and D, and it is obtained from the following formula:

$$d_{\Delta}(C,D)=(\text{number of concordant pairs})-(\text{number of discordant pairs}) \quad (4\text{-}11)$$

Notably, any pair of observations $(c(e_i),d(e_i))$ and $(c(e_j),d(e_j))$ are considered to be concordant if the ranks for both elements agree to each other: i.e., if both $c(e_i)>c(e_j)$ and $d(e_i)>d(e_j)$ or if both $c(e_i)<c(e_j)$ and $d(e_i)<d(e_j)$. On the other hand, they are considered to be discordant, if $c(e_i)>c(e_j)$ and $d(e_i)<d(e_j)$ or if $c(e_i)<c(e_j)$ and $d(e_i)>d(e_j)$. But if $c(e_i)=c(e_j)$ or $d(e_i)=d(e_j)$, then the pair is neither concordant not discordant.

4.2.3 General consistency measure

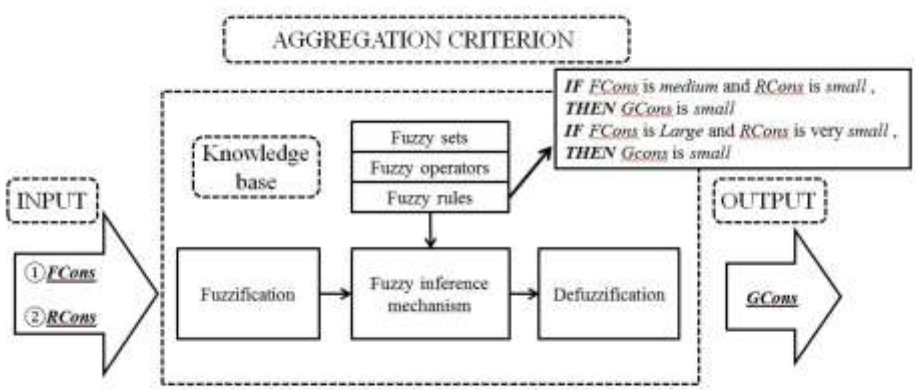


Figure 4 - 10 AC constituted based on a fuzzy inference system

Finally, an aggregation criterion (*AC*) is required to integrate the previous two indices, *FCons* and *RCons*, so as to constitute a general consistency measure (*GCons*) to investigate the overall relations between the two sensory modalities. This criterion should be both robust to noise and easy for knowledge interpretation. For this purpose, a fuzzy inference system [WANG, 2009] is designed and illustrated in Figure 4-10. This system consists of three major parts responsible for the fuzzification of input data, fuzzy operation based on fuzzy rules, and defuzzification to produce output data, respectively.

Table 4 - 13 Fuzzy rules for generating AC

RCons \ *FCons* (*GCons*)	*VS*	*S*	*M*	*L*	*VL*
VS	*VS*	*VS*	*VS*	*VS*	*VS*
S	*VS*	*S*	*S*	*S*	*S*
M	*VS*	*S*	*M*	*M*	*M*
L	*VS*	*S*	*M*	*L*	*L*
VL	*VS*	*S*	*M*	*L*	*VL*

As mentioned in Chapter 3, fuzzy rules are crucial for building a fuzzy inference system. In the current study, discussions were carried out among a panel of six experts to design a fuzzy-rule table as follows (Table 4-13).

In this table, *VS*, *S*, *M*, *L*, *VL* denote the linguistic values of '*Very small*', '*Small*', '*Medium*', '*Large*' and '*Very Large*', respectively. Every cell in this crosstab can be expressed as a fuzzy rule, for example:

IF *FCons* is *medium* (*M*) and *RCons* is *small* (*S*), ***THEN*** *GCons* is *small* (*S*).

Each linguistic expression is equivalent to a numerical value ranged from 0 to 1 according to the fuzzy membership function defined for each input and output variable during the process of fuzzy inference. The membership function is illustrated in Figure 4-11. It is a commonly used function uniformly distributed on [0, 1].

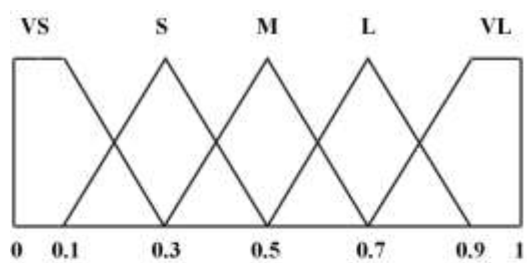


Figure 4 - 11 Fuzzy membership function for input and output

After applying the aggregation criterion, a general consistency measure (*GCons*) was constituted to investigate the extent to which the tactile properties can be transmitted through different visual representations of a textile product, with both the classification consistency and the distribution similarity taken into consideration.

4.3 Visual interpretation of fabric tactile properties

The proposed approach is applied to the sensory data obtained from different experimental scenarios. In this section, we present the application results with respect to fabric tactile descriptors and samples, followed by a profound discussion on the major observations.

4.3.1 Results on descriptors

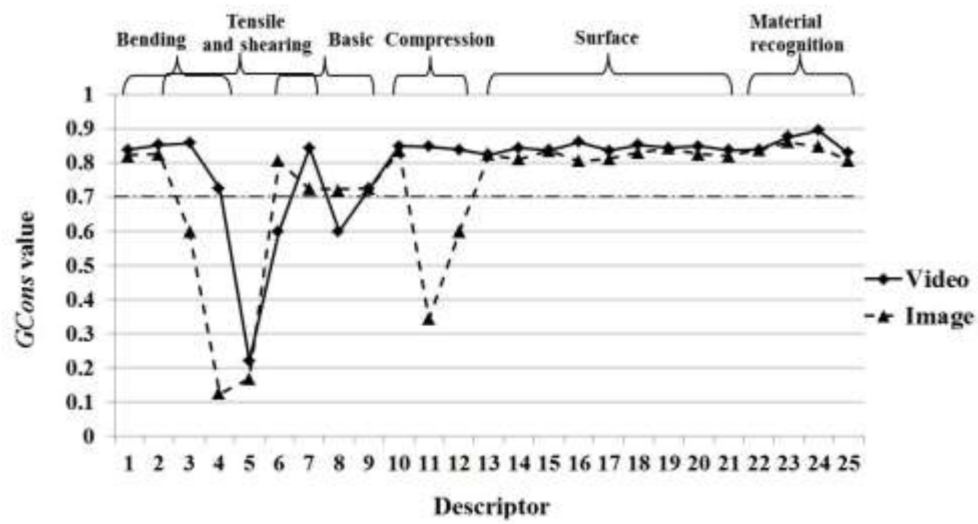


Figure 4 - 12 GCons values on video and image observations (on descriptors)

As mentioned in the previous section (Section 4.2.1.1), the visual observations are considered as the condition attribute set, while the real-touch observations as the decision set. Taking the real-touch observations as a reference, the computed *GCons* values for the video and image data are depicted as the so-called ‘perceptual lines’ in Figure 4-12, where the solid line represents the video results and the dash line the image results.

According to the overall distribution of the computed *GCons* results for both image and video scenarios, we draw a horizontal line at the value of 0.7 and name it as ‘satisfaction line’ (shown in dash-dot line). As we can see from this figure, there are a significant amount of descriptors (18 out of 25) for whom the *GCons* values of both the video and image observations are higher than

0.7 . This indicates that a big part of the tactile properties can be well interpreted through some specific visual representations of the textile products being concerned.

Table 4 - 14 Statistics of visual observations (on descriptors)

Index	Video			Image		
	Overall (D1~D25)	Left (D1~D12)	Right (D13~D25)	Overall (D1~D25)	Left (D1~D12)	Right (D13~D25)
MEAN	0.788	0.742	0.830	0.722	0.624	0.813
STDEV	0.136	0.182	0.049	0.199	0.252	0.041

It can be observed from the line shapes that on most of the descriptors the solid line has a more stable shape than the dash line with fewer fluctuations, which indicates that the panellists in the video scenarios have more stable and accurate performance as compared with those in the image scenarios. This is in accordance with the statistics shown in the two columns labelled 'Overall' in Table 4-14 that, through all the twenty five descriptors, the video observations have a higher mean value (0.788) and lower standard deviation (*STDEV*) value (0.136) than the image observations (0.722 and 0.199, respectively).

Table 4 - 15 Distribution of E-L points

E-L Point	Low in both	Low in video	Low in image
D4 (Wrinkle-resistance)			×
D5 (Drape)			×
D6 (Stretchiness)	×		
D7 (loose-tight)		×	
D9 (Thin-thick)		×	
D12 (Springiness)			×
D13 (Fullness)			×

Besides, Table 4-15 shows the extremely-low (*E-L*) points (marked by "×") detected from the figure. It is found that the solid line has only three such points, while the dash line has four, which also means that the panellists in the video scenarios have a generally better assessing performance than those in the image scenarios.

Let's take a further look at the perceptual lines in Figure 4-12. For the left part of the figure, in which the descriptors concern fabric's mechanical and basic properties (from D1 to D12), both the solid and dash lines have generally more and bigger fluctuations than for the descriptors on the right part of the figure, which implies that the panellists in both the video and image scenarios tended to encounter bigger difficulties in perceiving these properties. This observation is reasonable, since in real-life experience, most of the properties falling in this group are evaluated through direct touch by hand such as stretching, grasping, bending, etc. But when touch is deprived as is the case in our visual experiments, the assessors are supposed to, in fact, make decisions based on the associated memory accumulated from previous touching experience. Thus, their judgment might be less accurate or even incorrect. For example, on the fifth descriptor pair 'stretchy—non-stretchy' (D5), an *E-L* value (see Table 4-15) is detected in both video and image scenarios, which indicates that both the available video and image displays fail to well recall the panellists' associated memory on this specific property.

However, by comparing the shape of the two perceptual lines, we still can see that the panellists in video scenarios performed generally better than those in image scenarios. This observation can be confirmed by the statistics shown in columns labelled 'Left' in Table 4-14 that, for this part of descriptors, the video observations have a higher *MEAN* (0.742) and lower *STDEV* (0.182) than the image observations (0.624 and 0.252, respectively), which indicates that there are more descriptors in this part for whom the *GCons* values of video scenarios are higher than their counterparts in image scenarios. We can find the descriptors D3 (Drape), D4 (Wrinkle resistance), D11 (Springiness) and D12 (Fullness) as good examples. This phenomenon is not hard to understand. Compared with static photos captured from a limited number of angles, video clips can record information about an object from every possible angle and in a continuous way just as the object is viewed in the real case. As we have discussed previously, the more the visual information about the skirts is available, the more the so-called associated memory, which plays a crucial role in the non-haptic evaluation of fabrics' tactile properties, will be recalled by our brain. In this situation, it is not surprising that the panellists tend to make more correct judgments about fabrics' mechanical and some basic properties through samples' video clips than through static images.

However, there are still some exceptional cases. On some descriptors concerning fabrics' basic properties such as 'loose—tight' (D6) and 'thin—thick' (D8), the panellists in image scenarios have higher evaluation accuracy than those in video scenarios. The reason behind can be that static images are supposed to provide clearer and more stable reveals about some fabric details of which the evaluation is more dependent on a careful visual observation.

On the other hand, for the descriptors concerning fabric's surface characteristics (from D13 to D21) and material identification (from D22 to D25) whose results are depicted on the right part of Figure 4-12, both two perceptual lines (for video and image scenarios, respectively) are comparatively stable in the shape and situated above the satisfaction line. As is shown in the columns labelled 'Right' in Table 4-14, for the descriptors in this part, the *MEAN* values for image and video observations are both quite high (image: 0.813; video: 0.830) while the *STDEV* values are both very low (image: 0.041; video: 0.049). Besides, no big difference is detected on the values of these two indices between different scenarios. All these indicate that although the panellists could not really touch the fabric, they are still able to perceive most of its surface properties with certainty, and well identify the materials of the samples through their video or image displays, which is in accordance with our daily life experience. Fabrics' surface characteristics originate from their weave, yarn thickness, yarn density and so on. Actually, as has been discussed in Chapter 2, these parameters are visible via diffusely reflected light which comes from (1) at the surface layer of fibres and (2) between surfaces of internal fibres. As we view a real textile sample, the light reflected diffusely stimulates our eyes and provides two-dimensional colour images on our retinas as an image of the woven construction, at which point our brain registers a three-dimensional image by way of recognizing memories of experiences with fabrics, which is a typical kind of memory association. And the material of the sample will be determined as at the second level of this memory association. According to our experimental results, in the current study, the panellists were not able to view the real samples, but the corresponding visual (video or image) representations are believed to have made these reflected light of importance truly recorded.

4.3.2 Results on samples

The *GCons* values are also computed on the six sample skirts, as illustrated using a radar plot in Figure 4-13.

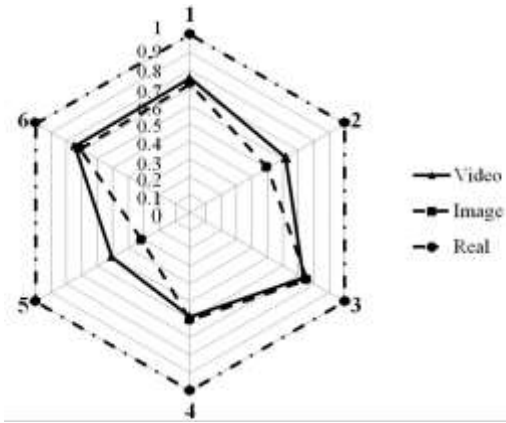


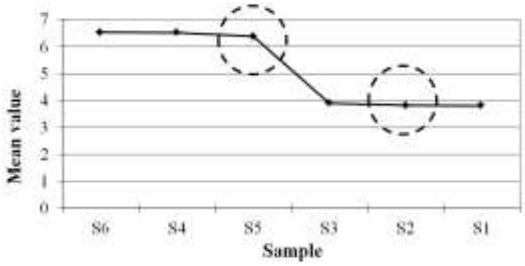
Figure 4 - 13 GCons values on video and image observations (on

In this figure, the solid, dash and dash-dot lines correspond to the video, image and real-touch data (as a reference), respectively. After calculating the *Mean* and *STDEV* values (see in Table 4-16) of the *GCons* results on samples, similar observations are obtained that the panellists in video scenarios have comparatively better performance than those in image scenarios.

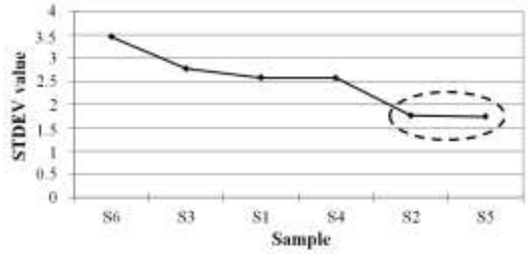
Table 4 - 16 Statistics of visual observations (on samples)

Index	Video	Image
Mean	0.657	0.601
STDEV	0.103	0.169

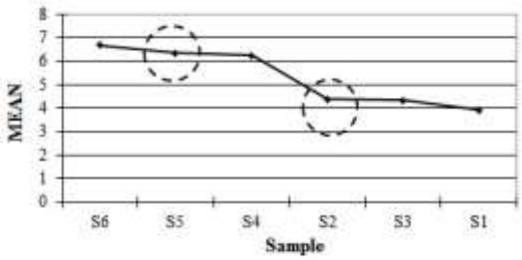
There are two special samples, S2 and S5, whose *GCons* values are both relatively low. To figure out the reason, more investigation should be done on the raw evaluation data of these two samples. After calculating the *Mean* and *STDEV* values on all the descriptors for S2 and S5, some clues have been found. The statistic results are illustrated in descendant order and shown in Figure 4-14 and Figure 4-15.



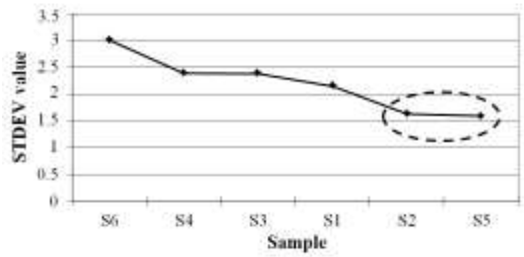
(a) Real-touch



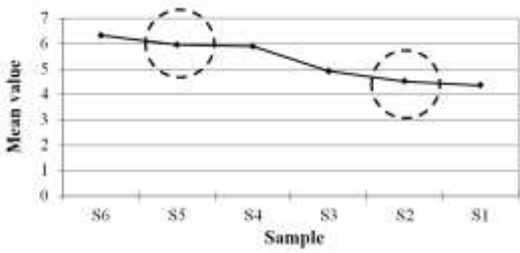
(a) Real-touch



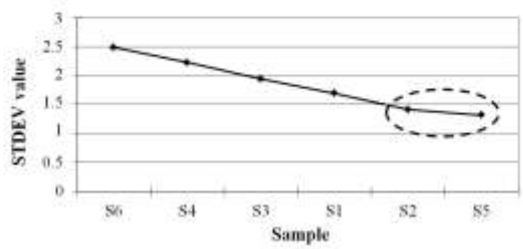
(b) Video



(b) Video



(c) Image



(c) Image

Figure 4 - 14 Mean values on raw data in three scenarios

Figure 4 - 15 STDEV values on raw data in three scenarios

It is evident that the *Mean* values of these two samples throughout the three experimental scenarios are at the median level, being neither very high nor very low. Meanwhile, the *STDEV* values of them are lowest among the six in all the three scenarios. It is easy to understand that a fabric with a median *Mean* value and a low *STDEV* value tends to have a very general performance, as compared with the others, on many tactile properties, without very prominent features to be easily recognized by the assessors. And these fabrics can often lead to uncertain judgment, especially in visual tests where the associated memories are recalled. In the current study, sample 2 and 5 obviously fall into this kind of fabrics.

4.4 Comparison with classical method

In order to study the relations between different datasets, some statistical methods are often used in many previous researches such as the multivariate analysis including PCA (Principal component analysis), factor analysis and regression analysis, and correlation analysis including canonical correlation, Pearson's correlation and rank order correlation [ANDERSON, 1998]; [WOLFGANG, 2007]. These classical methods have been widely applied to various kinds of sensory research.

The aim of the current study is to investigate the relations between the evaluation results obtained from different experimental scenarios on the same set of samples and with respect to the same group of tactile descriptors. Each referred relation is single-to-single and its two ends are definite (that is, between the real-touch observation and its counterpart in either video or image scenario on the same descriptor or sample). Therefore, the corresponding data analysis does not concern either the dimensional reduction of data space or the correlation between different variables inside each group. In this situation, PCA, factor analysis, regression analysis and canonical analysis are not applicable here. Instead, as one of the most used ways of correlation analysis, Pearson's correlation coefficient is employed as the representative of the classical methods to be compared with the novel approach proposed in our study.

4.4.1 Pearson's correlation coefficient

The Pearson's correlation coefficient on the *i*th descriptor is denoted as $r_i(V)$ and $r_i(I)$ for video and image data, respectively. For example, $r_i(V)$ is defined as follows.

$$r_i(V)=\frac{\sum_{j=1}^{m}\left(v_i(e_j)-\overline{v}_i\right)\left(t_i(e_j)-\overline{t}_i\right)}{\sqrt{\sum_{j=1}^{m}\left(v_i(e_j)-\overline{v}_i\right)^2}\sqrt{\sum_{j=1}^{m}\left(v_i(e_j)-\overline{v}_i\right)^2}},\quad m=6, n=27$$

$$\begin{cases} |r_i(V)|=0, & \text{no linear correlation;} \\ |r_i(V)|<0.4, & \text{low linear correlation;} \\ 0.4\le |r_i(V)|\le 0.7, & \text{significant linear correlation;} \\ 0.7\le |r_i(V)|<1.0, & \text{high linear correlation;} \\ |r_i(V)|=1, & \text{perfect linear correlation.} \end{cases}$$

4.4.2 Results

Figure 4-16 and Figure 4-17 show, on descriptors and on samples respectively, the computed values of Pearson's coefficient for the video and image observations as compared with the real-touch ones. The solid lines represent the video results while the dash lines the image results.

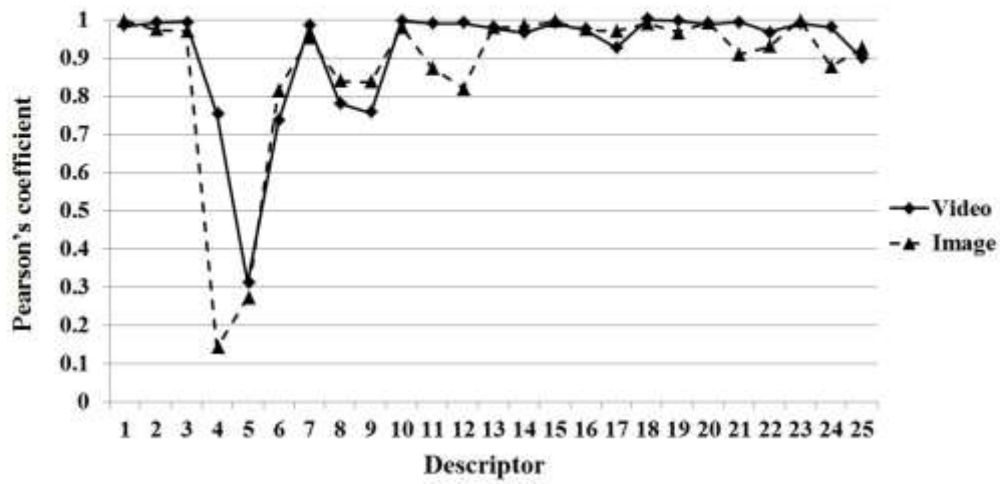


Figure 4 - 16 Pearson's coefficients on video and image observations (on descriptors)

After a comparison with the results obtained from our proposed approach (shown in Figure 4-12 and Figure 4-13), some important observations are obtained as follows.

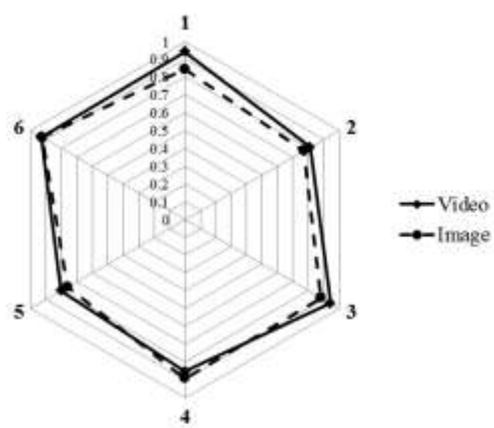


Figure 4 - 17 Pearson's coefficients on video and image observations (on samples)

(1) The correlation results are quite polarized which is especially obvious for results on descriptors (Fig. 11). It is indicated that, as compared with our proposed approach, the linear correlation method is not robust enough. Pearson's correlation coefficient is very sensitive to

outliers. Actually, just like many linear methods, a reliable correlation analysis has two basic requirements on the research objects, first, normal distribution; second, a lot of samples. But these two requirements cannot be met in the current study. From such a small number of samples, it is very difficult to acquire robust results. In this situation, our proposed approach has a big advantage over the correlation method in that it is based on the analysis of data structure, thus no special requirements are set on the distribution and size of the datasets. And of course, the results are supposed to be more robust.

(2) Different from the results obtained by our new approach, there is a big amount of descriptors on which the correlation values are indiscernible between video and image observations. Similarly, for all the six samples, no evident difference is detected between video and image data on the Pearson's coefficient. It is therefore assumed that there is a big information loss during the analysis. Pearson's correlation coefficient is a measure of the degree of linearity between two variables. But linear correlation is just one among many complicated relations that can exist between two datasets especially when the problem is concerned with sensory issues as is the case in the present study. Since nonlinear relations could not be completely explained by correlation analysis, it is not surprising that the actual difference between the datasets is not clarified using this method. On the contrary, since the new approach is put forward based on the theories of fuzzy sets and rough sets, it is quite capable of exploring nonlinear relations between different datasets and reduce information loss during data processing.

Besides, similar to many statistical methods, the whole process of the correlation analysis is invisible. The final results are not easy to understand. As a comparison, our approach follows a clear logic to find out the relations between different sensory datasets, from which the obtained results can be quite interpretable and reliable.

Therefore, from the above discussion, it is believed that to solve the problem in the current study, our new method is more efficient than classical techniques because it can lead to robust, clear and interpretable results while being safe to use a small and randomly distributed sample set.

4.5 Conclusion

In this chapter, we attempted to measure the consistency of visual perceptions to real-touch perceptions of fabric tactile properties. For this purpose, in the first place, a series of sensory experiments have been designed and carried out in a strictly scientific and standardized way.

Then, as the crucial part of the study, a novel approach based on the combination of rough sets and fuzzy sets theory has been proposed to investigate from the evaluation data sets the extent to which the fabric tactile properties can be transmitted through some specifically designed visual representations of a number of textile products.

The results obtained from this study have confirmed that a big part of the fabric tactile properties in our daily life can be interpreted through some specifically designed visual displays (in either video or image forms). But generally speaking, video displays can provide more comprehensive and accurate information about fabric hand than image displays, since in the videos, both the dynamic and static effect of fabrics can be well expressed. These conclusions are of great significance for the study in Chapter 5. Since it has been confirmed that visual interpretation is feasible, it is possible to further explore the interpretative mechanism of visual perception of fabric tactile properties. Besides, some observations in the current study can work as guidance for the design of new experiments (Experiment II) in Chapter 5. For example, although panellists tend to perform better in video scenarios, some tactile properties (such as thickness and tightness of the fabric) are better illustrated through image representations. Thus, in the new experiments, it is decided that both video and image displays will be present in visual evaluations in order to provide the panellists with most possible visual information about the samples.

Finally, after being compared with conventional linear correlation method, the new approach developed in the current study is proved to be more competent in solving the problem of discourse Its framework has set an example to the standardized resolution of similar problems in the future. This approach is applied initially in the textile domain, but it can be quite helpful in solving many other problems as long as they are concerned with difference analysis on multiple-sourced data. Especially, due to its high capacity in dealing with data imprecision and uncertainty, this approach will be found more useful in solving sensory related problems.

CHAPTER 5: Visual interpretative mechanism of fabric tactile properties (Experiment II)

In the previous chapter (Chapter 4), we have found that most of fabrics' tactile properties can be well interpreted through some specifically designed visual representations. On this basis, here, in this chapter, we are going to unveil the mechanism lying beneath this finding, which we call the interpretative mechanism of visual perception of fabric tactile properties. A new round of sensory experiments have been designed and carried out on more textile samples to obtain, on one hand the visual features of the sample skirts, and on the other hand the fabric tactile properties through real-touch evaluations.

As regards to the data analysis, two major steps should be taken to investigate the so-called interpretative mechanism. The first step is to find for each tactile property the visual features that have the most significant impact. From the computational point of view, this step is in fact the process of feature selection which is aimed to reduce the complexity of the system. Being different from mechanical measurements, there exists frequent and widespread sensory cooperation during human perception. So, the sensory relations to be concerned in this study involves two aspects, one is the single-to-single relations between one tactile property and any visual feature; the other is the multiple-to-single relations between one tactile property and several principal visual features, Mathematically, the single-to-single relations are measured by using our approach which has been proposed in Chapter 4; while the multiple-to-single relations are examined by applying proper modifications to our approach.

The first step is aimed to discover the basic structure of the visual interpretative mechanism, on this basis, the second which is also the final step of our entire study is to quantify this mechanism by establishing an inputs-output model between each fabric tactile property and the corresponding principal visual features. In the study, this model is developed as an Adaptive Network-based Fuzzy Inference System (ANFIS). This system has absorbed the advantages of both neural network and fuzzy inference system in data learning as well as knowledge interpretation. By setting up intuitively reasonable initial membership functions, a learning process is launched to generate a set of fuzzy if-then rules to describe the input-output behavior of the data system. With the help of this model, it will be possible to predict fabrics' tactile properties from perceived visual features of the samples with a satisfactory accuracy. So far, the so-called visual interpretative mechanism has been unveiled.

5.1 Sensory experiments (Experiment II)

In Experiment I, we have found that it is possible to perceive with certainty fabric tactile properties through samples' visual representations, which provides ground for the further study on the visual interpretative mechanism in this chapter. Besides, Experiment I has set an example for acquiring sensory data in a standardized way and developed a novel and efficient approach which is the essence of our systematic methodology, to study the complex sensory relations concerned in the study. Thus, we can say that Experiment I is fundamental for our entire research system and at the same time it serves as the initial experiment for Experiment II.

Table 5 - 1 Fabric details of the twelve new samples

Sample	Fabric content	Weave structure	Weight (g/m^2)
S7	100% Cotton	Twill	421.3
S8	55% Ramie 45% Cotton	Plain	189.5
S9	100% Polyester	Plain	31.70
S10	100% Cotton	Twill	410.3
S11	97% Cotton, 3% Spandex	Plain	209.6
S12	100% Polyester	Plain	373.2
S13	65% Linen, 35% Cotton	Plain	199.4
S14	100% Polyester	Satin	110.1
S15	100% Silk	Satin	68.90
S16	85% Cotton, 15% Polyester	Plain	452.1
S17	100% Cotton	Plain	157.8
S18	100% Polyester	Plain	30.20

5.1.1 Sample preparation

On the basis of the six samples in Experiment I, we add twelve more textile fabrics with various tactile properties into the new round of experiments. Some fabric details are shown in Table 5-1. These twelve fabrics are made into flared skirts of the same design and production specifications as the six samples in Experiment I. Hence, we now have in total eighteen samples in Experiment II.

A girl of the best-fit body size was invited as the mannequin to wear these samples and make static postures and dynamic movements according to the researcher's design. Training was required before recording.

Video clips and multi-angle photos are created for these new samples in the same way as the six initial samples. Figure 5-1 shows an example of the visual representations (multi-angle photos and a screenshot of the video clip) of sample 16 (S16)

Multi-angle images

Video

Figure 5 - 1 An example of visual representations (for S16)

5.1.2 Experiments

Two sensory tests, denoted as Exp. (a) and Exp. (b), are involved in Experiment II aimed to evaluate the samples' tactile properties and the visual features, respectively.

5.1.2.1 Evaluation of fabric tactile properties (Exp. (a))

(1) Panel

In this session, a panel of ten experts with textile background (including lecturers, researchers, PhD students and postgraduate students from textile domain) were invited to take part in the evaluation of fabric tactile properties of the textile samples. All these panelists have previously participated in at least twice subjective tests concerning the evaluation of textiles' tactile properties.

(2) Standardized sensory methods

(i) Choice of sensory descriptors

The sensory descriptors to be used in this part of the experiment are selected from the twenty one tactile descriptors in Experiment I. What is worth mentioning is that, strictly speaking, the last four (D22~D25) out of the twenty five descriptors in Experiment I are not really about fabrics' tactile properties. Their involvement was for the purpose of comprehensively understanding the panelists' capacity in recognizing fabrics in non-haptic environment. So, in this session, these descriptors are eliminated from our consideration.

Visible and invisible tactile properties

In fact, the twenty one tactile descriptors can be divided into two categories, *visible* and *invisible*, according to their direct accessibility by vision. In the category of *visible*, we, firstly, include eight descriptors concerning fabrics' surface properties, i.e., from D13 to D20. The different surface textures perceived by the panelists during touch originate from the fabrics' geometric characteristics, such as natural convolution of fibers, cross-sectional shapes of fiber, twists of yarns, surface fluff and so on. Actually, as we have discussed in the previous context (Chapter 2), these characteristics can also be perceived by our eyes. For different fabric samples, incident light beams are scattered at different strengths in different directions according to the specific surface geometry. When a panelist views a fabric sample, the diffusely reflected light would stimulate the panelist's eyes and provide two-dimensional color images on the panelist's retinas as a description of the sample's surface characteristics, at which point the panelist registers a three–dimensional image by way of recognizing memories of experiences with fabrics. This is a typical process of the so-called memory association we have mentioned in the previous section. In this sense, we call these eight descriptors visible. Besides, there are another two properties which can also be considered as visible. One is the mechanical property 'Draped—non-draped' (D3); the other is the basic property 'thin—thick' (D8). Similarly, these two properties are directly measurable via vision. The evaluation of the drape of a fabric sample is highly related to the silhouette of the skirt it is made into. And the thickness of a fabric can easily be judged through direct visual observation.

Otherwise, the left eleven tactile descriptors concerning fabrics' mechanical properties (D1, D2，D4, D5, D6, D7, D10, D11, and D12), certain basic and surface properties (D9 and D21) fall into the category of *invisible* due to the fact that they cannot be directly measured by visual observation.

In this part of the experiment, the eleven invisible descriptors are selected to represent the tactile dimensions of the eighteen samples, which are listed in Table 5-2.

Table 5 - 2 Eleven invisible tactile descriptor pairs

Nm.	Descriptor pair	Nm.	Descriptor pair
D1	Stiff—pliable	D9	Light—heavy
D2	Dead—lively	D10	Soft—hard(in compression)
D4	Crumply—wrinkle-resistant	D11	Non-springy—springy
D5	Non-stretchy—stretchy	D12	Non-full—full
D6	Loose—tight	D21	Warm—cool
D7	Flimsy—firm		

(ii) Sensory evaluation techniques and scale

The same definitions and gesture instructions as those in Experiment I are applied in the current tests for the evaluation of fabric tactile properties. An eleven-point intensity scale is used in the evaluation as referred to in Table 4-8.

(iii) Training

The panelists in this experimental session were asked to evaluate samples' tactile properties in a real-touch environment (vision is allowed during evaluation as is the case in real-life purchasing). A similar training session as the one in Experiment I was carried out by the panelists before real tests. That is, a six-hour instruction was given to help the panelists get clear with the major purpose of the sensory tests and all the concerned evaluation techniques. Another six hours were arranged for the panelists to practice the evaluation gestures, techniques and procedures with a set of training samples.

(3) Sensory experiment

Given that the six initial samples (S1 to S6) have already been evaluated in Experiment I, in order to keep the entire eighteen samples in the same evaluation system, the evaluation results of the six samples are kept and taken as references during the evaluations of the twelve new samples in this session.

In practice, before the tests, all the samples were conditioned for a minimum of 24 hours under the standard atmospheric condition (20±2 C temperature, 65±2% relative humidity). And the entire experiment was done in a laboratory satisfying this condition. The evaluation results of the first six samples were recorded and marked on the evaluation scale as reference for each tactile descriptor. Figure 5-2 is an example of such a reference scale (for 'stiff-pliable'). The reference scales for all the eleven tactile descriptors are put together in a table on a page of paper called 'reference sheet'.

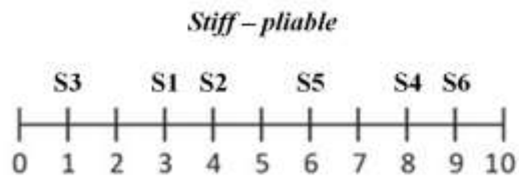


Figure 5 - 2 Reference scale for 'Stiff—pliable'

During the tests, the eighteen samples were laid on a big desk in two rows. The upper row laid the first six samples, while the lower row laid the other twelve samples. Each panelist was given a reference sheet and asked to give scores between 0 and 10 according to the comparison between current sample and the six reference sample on the specific tactile property. For example, according to the panelist, if current sample is stiffer than S1 but more pliable than S3, he may give two as the score of the sample on descriptor pair 'stiff—pliable'. It is believed that this comparative evaluation is less time consuming, easy to follow, and tends to obtain more concrete and reliable answers from the panelists. Similar to Experiment I, the evaluation in this session should be carried out individually for each panelist.

Before getting started, the panelist would be asked to wash and dry his/her hands with the non-moisturizing soap and paper towel provided. The panelist might start the evaluation when he/she was ready. No time limit is set for the sensory tests.

5.1.2.2 Evaluation of visual features (Exp. (b))

(1) Panel

Five professionals were recruited from the apparel industry to evaluate skirts' visual features. All these panelists have profound experience in evaluating the appearance of apparel products according to their professional knowledge and standard criteria.

(2) Standardized sensory methods

(i) Choice of sensory descriptors

The aim of this part is to produce an exhaustive list of descriptors in order to cover as comprehensively as possible the visual features of the concerned skirts. These descriptors are supposed to be directly captured through vision and express the premier and basic information about the samples' external features. To be specific, they should be composed of two aspects. One is the appearance characteristics about the skirts, while the other is the visual characteristics about the fabrics. To generate descriptors of the first aspect, a procedure similar to the one in Experiment I (Section 5.1.2.1) was designed and implemented. Some redundant descriptors were screened out after several discussions. Meanwhile, a literature study was necessary to make sure that the selected descriptors are generally in consensus with the commonly accepted terminology. In this way, twenty eight descriptors concerning both the static and dynamic effects of the sample skirts are determined.

As introduced previously in Section 5.1.2.1, fabrics' tactile properties can be classified into two categories, visible and invisible, namely. The ten tactile descriptors concerning fabrics' surface properties, drape, and thickness which are taken as visible, are determined as the other aspect of samples' visual features. Since the descriptor 'Draped—non-draped' is included in both two visual aspects, thirty seven visual descriptors are finally determined in this study. As are shown in Table 5-3 (a) and (b), these descriptors are categorized according to their descriptive positions.

(ii) Sensory evaluation techniques and scale

For each visual descriptor, a detailed definition with a graphic illustration (shown in Figure 5-3) was available to the panelists. An eleven-point intensity scale is used in the evaluation as referred to in Table 4-8. For example, if the silhouette of a specific sample is very fit to the mannequin, then the panelists may give nine as the score on the descriptor E18, so on and so forth.

Figure 5 - 3 Graphic illustration of some parts of the skirt

Table 5 - 3 (a) Visual features of sample skirts (E1-E19)

Position	Nm	Feature	
Waist line	E1	Outline of pleats	Clear—Fuzzy
	E2	Outline of pleats	Rigid—Soft
Abdomen and huckle	E3	Fitness to body shape	Unfit—Fit
	E4	Pleat size	Small—Big
	E5	Pleat distribution	Uneven--Even
	E6	Appearance	Unnatural--natural
Lower part of skirt	E7	Expending extent from below the hip	Not expanding--Expanding
	E8	Wave size	Shallow--Deep
	E9	Wave smoothness	Non-smooth--Smooth
	E10	Wave distribution	Uneven--Even
	E11	Wave-height consistency	Inconsistent--Consistent
	E12	Bottom-edge evenness	Uneven--Even
	E13	Curling extent of bottom edge	Non-curling--Curling
Color	E14	Brigntness	Dark--Light
	E15	Vividness	Muddy--Vivid
	E16	Temperature	Cool--Warm
luster	E17	Light intensity	Weak--Strong
Silhouette	E18	Fitness	Unfit--Fit
	E19	Shapability	Incorrect--Correct

(iii) Training

A training session is also needed in the current sensory tests. A general introduction has been given to the panelists on the major purpose of the experiment. A detailed instruction with illustrative examples helps the panelists get familiar with the concerned evaluation techniques, and the standardized evaluation procedures to be followed in the real tests. This training session took about 6 hours.

Table 5-3 (b) Visual features of sample skirts (E20-E37)

Position	Nm	Feature	
Silhouette	E20	Drape	Badly--Well
	E21	Overall outline	Rigid--Soft
Dynamic	E22	Balance	Badly--Well
	E23	Following capacity	Badly--Well
	E24	Clinging	Badly--Well
	E25	Ethereality	Badly--Well
	E26	Wave flowability	Badly--Well
	E27	Swinging range	Small--Big
	E28	Rhythm	Badly--Well
Fabric	E29	Rough—smooth(overall feeling)	
	E30	Grainy—non-grainy	
	E31	With ridges—without ridges	
	E32	Bumpy—non-bumpy	
	E33	Prickly—non-prickly	
	E34	Fuzzy—non-fuzzy	
	E35	Non-slippery—slippery	
	E36	Harsh—soft	
	E37	Thin--Thick	

(3) Sensory experiment

As already illustrated in the previous context, on the basis of the observations from Experiment I, it is decided that, in the current session, both the video and image representations are made available for the panelists to acquire as much visual information as possible.

The visual display conditions and parameters are set as the same with the visual evaluation tests in Experiment I. The panelists are required to conduct the tests individually. During the evaluation, the panelists are totally free to refer to any visual sources that they want at any time. Besides, as the same with Experiment I, they are allowed to control by their own the playback of the video clips, or zooming in/ out the photos so as to obtain the desired observing accuracy. No time limit is set for the evaluation tests.

5.1.3 Mathematical formalization

After the above experiments, we have obtained, for each evaluation scenario, a matrix of aggregated sensory data, in which any element represents, for a specific sample (denoted in columns), the average evaluation value on the corresponding descriptor or attribute (denoted in rows) through all the panelists.

To be specific, for the evaluations of fabric tactile properties and visual features respectively, the corresponding data matrices are formalized as T and Q as follows,

$$T=\begin{bmatrix} t_1(e_1) & t_2(e_1) & \cdots & t_n(e_1) \\ t_1(e_2) & t_2(e_2) & \cdots & t_n(e_2) \\ \vdots & \vdots & \ddots & \vdots \\ t_1(e_m) & t_2(e_m) & \cdots & t_n(e_m) \end{bmatrix},\ Q=\begin{bmatrix} q_1(e_1) & q_2(e_1) & \cdots & q_l(e_1) \\ q_1(e_2) & q_2(e_2) & \cdots & q_l(e_2) \\ \vdots & \vdots & \ddots & \vdots \\ q_1(e_m) & q_2(e_m) & \cdots & q_l(e_m) \end{bmatrix}$$

in which, $U = \{e_1, e_2, \ldots, e_m\}$ is the set of samples, and m the number of samples. n denotes the nth tactile descriptor (as was well explained in Section 5.1.2.1 - (2) - (i), they refer to eleven invisible tactile properties, D1, D2, D4, D5, D6, D7, D9, D10, D11, D12 and D21, respectively), and l the number of visual feature descriptors. In the study, m=18, and $t_j(e_i)$, and $q_k(e_i)$ are the averaged evaluation scores (real numbers) varying between 0 and 10. ($i\in\{1, 2, \ldots, 18\}$; j = 1, 2, 4, 5, 6, 7, 9, 10, 11, 12, 21; and $k\in\{1, 2, \ldots, 37\}$).

5.2 Extraction of principal visual features

The ultimate objective of this chapter is to quantify the interpretative mechanism of visual perception of fabric tactile properties. Hence, there are two major problems to be solved in this study. The first problem is to discover the multiple-to-single relationships between the samples' visual features and the fabric tactile properties. On this basis, the second problem is to quantify these obtained relationships. Mathematically, to work out these two problems is in fact to operate the feature selection of the visual variables and then to set up an inputs-output model between visual and tactile data.

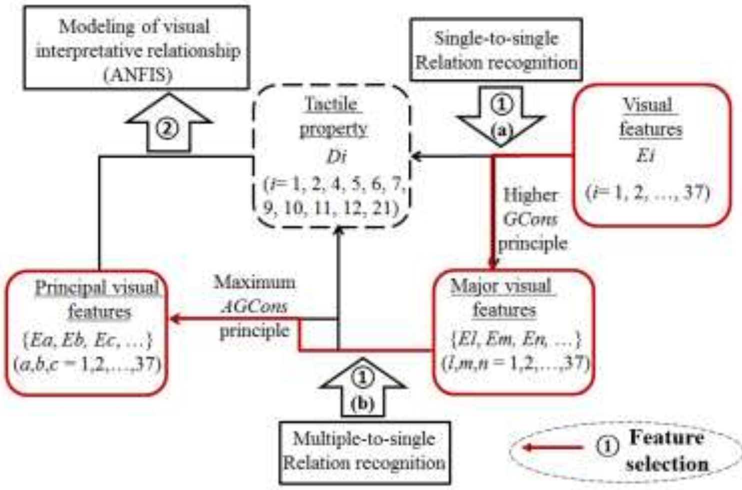


Figure 5 - 4 General framework of our methodology

Figure 5-4 shows a general framework of our methodology to explore the visual interpretative mechanism. In this figure, the part outlined in red denotes the solution of the first problem, that is, to recognize the multiple-to-single relationships between samples' visual features and fabric tactile properties (denoted by Di, (i= 1, 2, 4, 5, 6, 7, 9, 10, 11, 12, 21) signifying the so-called invisible tactile properties explained in Section 5.1.2.1 - (2) – (i)). In practice, it is aimed to extract a set of visual features who claim important impact on interpreting each tactile property. As is illustrated in Figure 5-4, two steps are involved in the solution. The first step is to define the basic points for computation. In our case, for a specific tactile property, its single-to-single relation (marked by ① (a) in the figure) with any visual feature is determined as one basic computing point. After this step, some visual features of major impact (denoted as *MF*'s) (El, Em, En,…, (l,m,n = 1, 2, …, 37)) are kept while others with minor impact are excluded for each tactile property, which will greatly reduce the complexity of the subsequent computation. On this basis, the second step, which is marked by ① (b), is to define a criterion to select principal variables (denoted as *PF*'s) (Ea, Eb, Ec, … (a,b,c = 1, 2, …, 37)) from the remaining visual features based on the exploration of the multiple-to-single relations for each tactile property with its major visual features.

Then, the part marked by ② represents the solution of the second problem, that is, to quantify the multiple-to-single relationships between any tactile property and its Principal visual features (denoted as *PF*'s). There, a fuzzy neural network, ANFIS, is developed to realize the modeling.

The above is a general illustration of the methodology we adopt to solve the problem of Chapter 5. Hence, in the current section, we are going to solve the first problem.

5.2.1 Study of single-to-single relations

Our approach proposed and illustrated in Chapter 4 is applied in this section to study the single-to-single relations between each fabric tactile property and any visual feature. According to our method, let $U=\{e_1,\ e_2,\ \cdots,\ \ e_{18}\}$ be the collection of samples. The results about the visible features and the invisible tactile properties from evaluating samples' visual representations are considered as the condition set and the decision set, respectively.

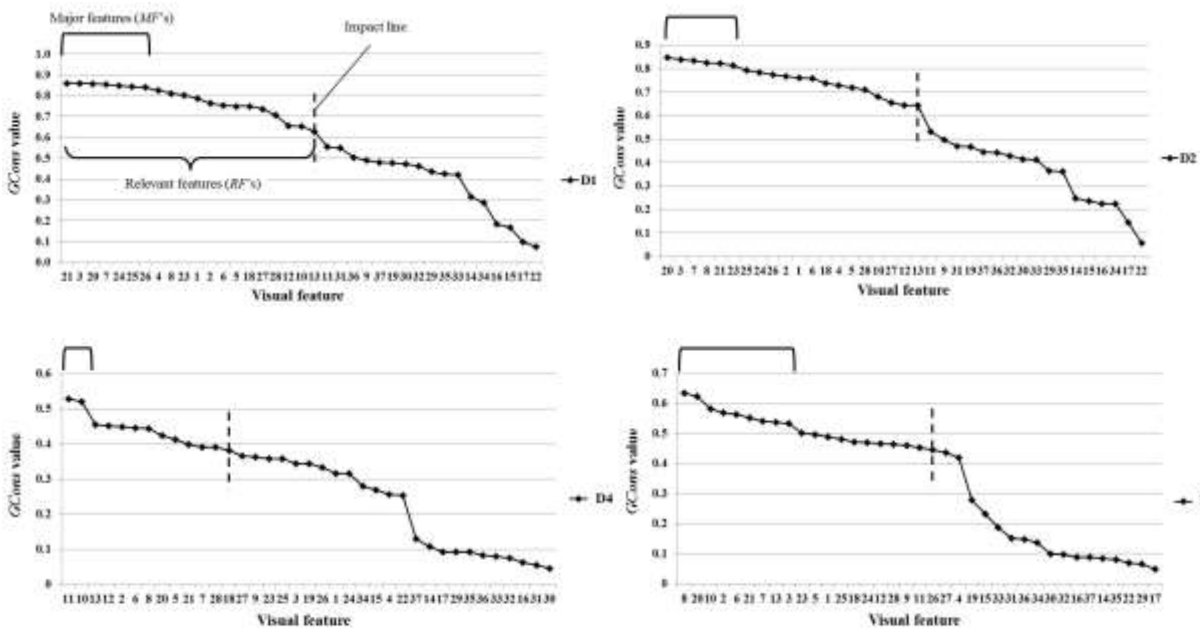


Figure 5 - 5 (a) Impact lines for the eleven tactile descriptor pairs (D1, D2, D4, and D5)

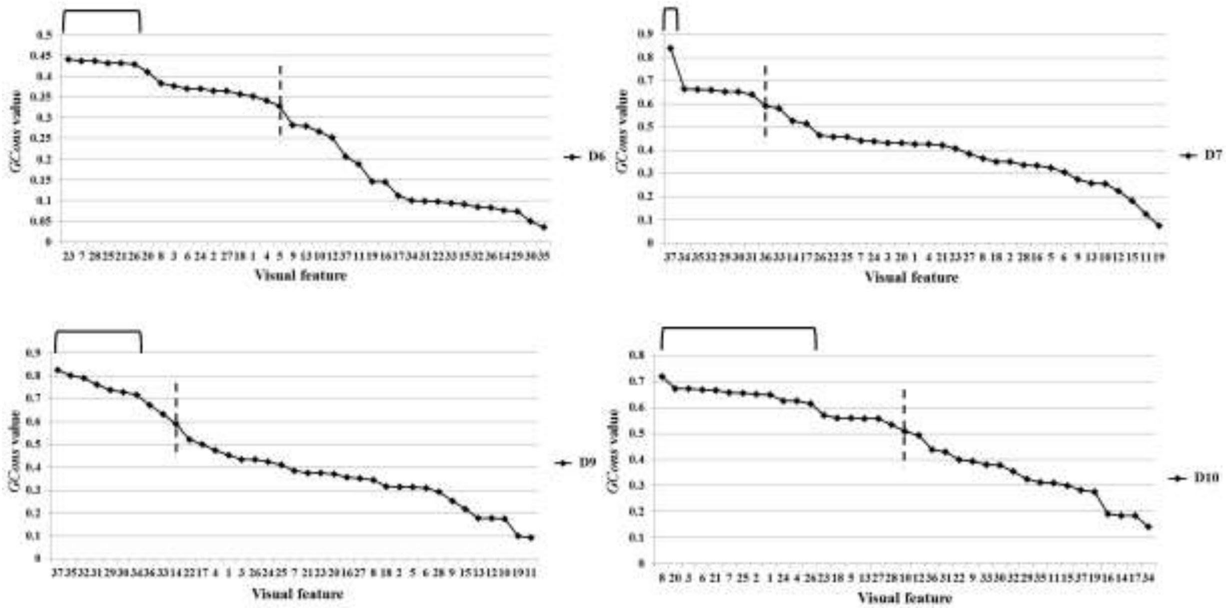


Figure 5-5 (b) Impact lines for the eleven tactile descriptor pairs (D6, D7, D9, and D10)

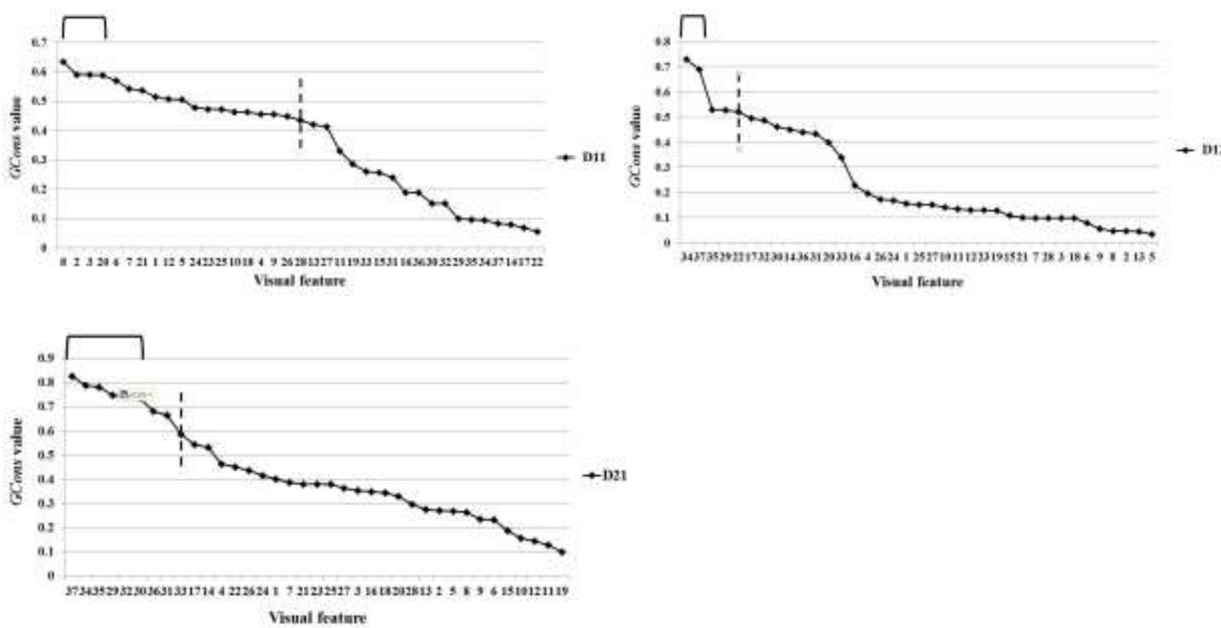


Figure 5-5 (c) Impact lines for the eleven tactile descriptor pairs (D11, D12, and D21)

For each invisible tactile descriptor (D#), a set of *GCons* values are computed on all the thirty seven visual features. Notably, those visual features that have higher *GCons* values are believed to be important in interpreting the corresponding fabric tactile property. The results are ranked in descending order and shown as so-called "Impact lines". Figure 5-5 (a), (b) and (c) show the impact lines of the eleven tactile descriptors.

Since for each pair of tactile descriptors, there are initially thirty seven visual features which have impacts to different extent on revealing the corresponding tactile property. In this part of the research, a stepwise screening has been taken, for each tactile property, to reasonably find out from such a big number of visual features the few ones that are of the highest significance. The first step is to remove the visual features that have obviously low impact. Those features left are called '*Relevant visual features*' (denoted as *RF*'s in the following discussion). On this basis, the next step is to further select the visual features that are believed to have the closest relation with the tactile property of interest. The features defined in this step are then called '*Major visual features*' (denoted as *MF*'s).

5.2.1.1 Selection of *RF*'s

As was mentioned previously, for each tactile property, the 'Impact line' depicts the degrees of relevancy of the thirty seven visual features in descending order. To select the *RF*'s for a specific tactile property is in fact to find out the visual features that have higher *GCons* values. (The fabric tactile properties to be concerned in this study refer to eleven invisible tactile properties selected according to the principles proposed in Section 5.1.2.1 - (2) – (i). To be specific, they are, D1, D2, D4, D5, D6, D7, D9, D10, D11, D12 and D21.)

For each tactile property, the highest *GCons* value computed from the thirty seven visual features is called its *Impact level* or *IL in short*. Graphically, on the impact line the visual features situated before the evident decrease (or steep slope, if any) discriminating the features with comparatively higher *GCons* values from those with lower values should be taken as *RF*'s for the corresponding tactile property. From a more formalized point of view, for a specific tactile property (invisible tactile properties selected according to the principles proposed in Section 5.1.2.1 - (2) – (i)) Dj, the visual feature Ei can be defined as an *RF* when the following condition holds,

$$GCons(i) \geq IL(j) \times w\left(w \in (0,1),\ i = 1,2,\cdots,k;\ j = 1,2,4,5,6,7,9,10,11,12,21 \right) \tag{5-1}$$

in which, k is the number of visual features (k = 37), w is the threshold for selecting the *RF*'s.

The determination of w should take into account the following two points:

(1) The selected *RF*'s should keep as many as possible the visual features with relatively higher *GCons* values. And on the other hand, those visual features whose *GCons* values are relatively low should be eliminated anyway.

(2) The point discriminating *RF'*s from the features with relatively lower *GCons* values should be close to the graphical discriminative point, that is the visual feature whose *Gcons* value represents the first dramatic decrease on the impact line

Therefore, in the current study, according to the distribution of the *GCons* results obtained from the eleven tactile properties and the above two basic determination rules, the value of *w* is decided as 0.7. By applying this threshold in Eq. (5-1), we have obtained for each tactile descriptor a series of *RF*'s. As is shown in Figure 5-5, on each impact line, a discriminating point has been marked by a vertical dash line (denoted as discriminating line). Those visual features situated before this line are taken as *RF*'s for the corresponding tactile property. We can see from the figures that the determination of *w* has, to a big extent, satisfied the above two rules. The increasing or decreasing of its value might cause the elimination of relevant features or might let in the visual features of relatively low relevancy to the corresponding tactile descriptor. Any of the above options will increase noise in the system.

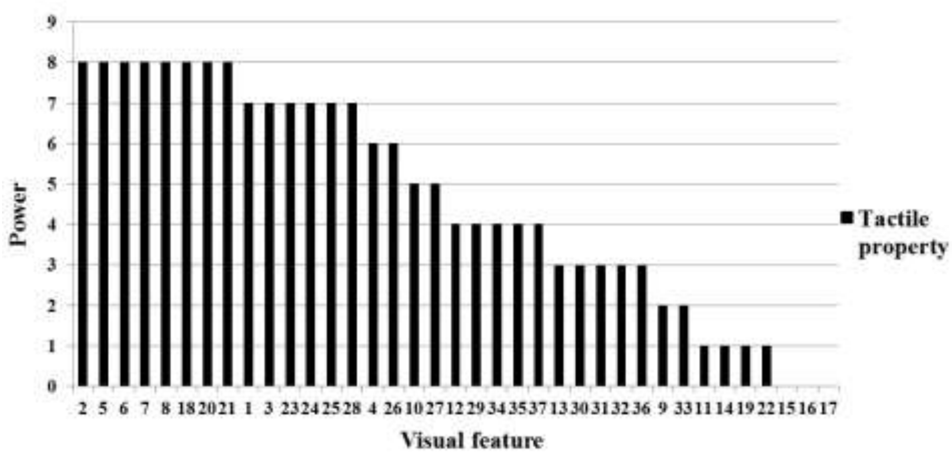


Figure 5 - 6 Power of thirty seven visual features

According to our definition, any visual feature whose *GCons* value is higher than seventy percent (or has a decrease of less than thirty percent) of the impact level is regarded as an *RF* of the corresponding tactile property. Taking D2 ('dead—lively') as an example, its impact level is the *GCons* value of E20, 0.848. Then the visual features whose *GCons* values are higher than 0.594 (0.848×70%), or graphically, on the impact line shown in Figure 5-5 (a), the visual features before (and including) E13 (*GCons* (13) = 0.643, and for the visual feature E11 which is after E13 on the impact line, *GCons* (11) = 0.531) are taken as the corresponding relevant visual features or *RF*'s.

For any visual feature, the number of the tactile properties which regard it as the *RF* is counted and called its *Power*. Figure 5-6 shows the thirty seven visual features ranked according to their strength of power in descending order. It is evident from this figure that almost every visual feature has a considerable impact on a range of tactile properties, which indicates that the thirty seven visual features are properly selected for the current study.

For better illustration in the following discussion, the eleven invisible descriptors are further categorized according to the properties they are aimed to reveal. The one is called "*Mechanical*" which contains seven descriptors concerning fabrics' bending, compression, tensile and shearing properties (D1 (Stiffness), D2 (Liveliness), D4 (Wrinkle-resistance), D5 (Stretchiness), D6 (Tightness), D10 (Compressive softness) and D11 (Springiness)). Then, the other category is called "*Constructional*" which includes the left four descriptors, i.e., D7 (Firmness), D9 (Weight), D12 (Fullness) and D21 (Surface temperature).

5.2.1.2 Discussions on mechanical properties

(1) Selection of Major visual features (*MF*'s)

Actually, for each tactile descriptor, there are several visual features, which have still higher *GCons* values among its *RF*'s constituting the so-called "Major-impact list". And these visual features are called "Major visual features" (denoted as *MF*'s). Here, we give the criterion for selecting the *MF*'s as follows.

For a specific tactile property, let $G = (g_1, g_2, \ldots, g_t)^T$ be the vector of *GCons* values of the *RF*'s in a descending order. We define the decreasing rate dr_i of any *RF* from the previous one on the sequence as:

$$dr_i = \frac{(g_{i-1} - g_i)}{g_{i-1}}, \quad (i = 2, 3, \cdots, t) \tag{5-2}$$

where t is the number of *RF*'s for the tactile property.

Thus, the average decreasing rate of the sequence is formulated as

$$\overline{dr} = \frac{1}{t}\sum_{i=2}^{t} dr_i \tag{5-3}$$

On the *RF* sequence, we find the *i*th *RF* whose decreasing rate dr_i is the first to exceed the average $\overline{dr}$. Then, we consider the *RF*'s before the *i*th *RF* (not including it) as the *MF*'s of the corresponding tactile property.

As an example, for D2, the corresponding average decreasing rate $\overline{dr}$ is 0.014. E25 is the first visual feature on the *RF* sequence whose decreasing rate dr_7 (=0.023) exceeds 0.014. Consequently, we select the first six visual features from the *RF* sequence, respectively E20, E3, E7, E8, E21 and E23, as the *MF*'s of D2. In the same way, the *MF*'s for the seven mechanical descriptors are extracted and marked by brackets above their impact lines as shown in Figure 5-5.

According to this criterion, for the seven mechanical properties, there are overall sixteen *MF*'s. For each *MF*, the number of mechanical properties under its power has been counted. The results for all the *MF*'s are ranked in a descending order and shown in Figure 5-7.

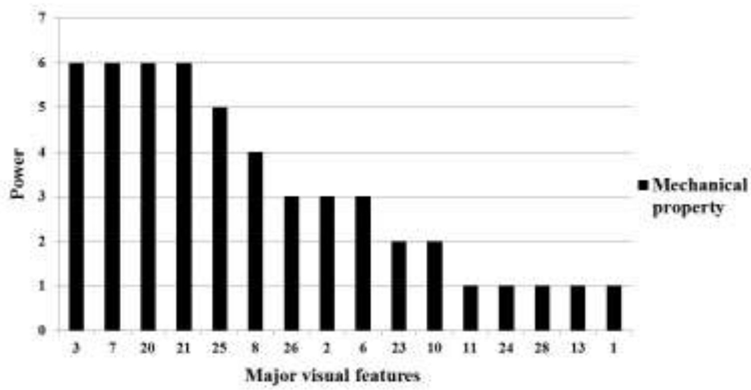


Figure 5 - 7 Power of major visual features

(2) Classification of Major visual features (*MF*'s)

Actually, according to the specific definition of each *MF* (seen in Table 5-3), these sixteen *MF*'s can be categorized into three major classes. The first class, which includes four *MF*'s (E3, E7, E20 and E21) expressing skirts' static outline features, is named "Macro-static features" (*MaS*'s). The second class contains seven *MF*'s (E1, E2, E6, E8, E10, E11 and E13) concerning skirts' detailed information such as the size, shape and distribution of the pleats and waves. This class is called "Micro-static features" (*MiS*'s). The remaining five *MF*'s (E23, E24, E25, E26 and E28) constitute the third class "Dynamic features" (*Dyn*'s)

As is obvious from Figure 5-7, among the ranked sixteen *MF*'s, the first four are *MaS* features referring to the fitness at the hip (E3), skirt's expanding degree (E7), drape (E20) and outline shape (E21), respectively. As an individual, each feature has impact on six out of eight fabric mechanical properties, which is called "impact-coverage". And working together, they have an overall impact-coverage of 87.5% (7 out of 8). In addition, the *MaS* features have comparatively larger impact-coverage than the other two classes of features. From this, we can assume that skirts' shaping effects are crucial elements among all the *MF*'s affecting fabrics' mechanical properties.

According to the previous classification criteria, there are eight *Dyn* features in the overall thirty seven visual features, five among which appear as the *MF*'s and have impact on five out of eight fabric mechanical properties. This indicates that skirts' dynamic effects are significant for reflecting fabrics' mechanical properties. Among these elements, the ethereality (E25) and wave flowability (E26), individually, are proved to be especially important, having their impact-coverage of 62.5% and 37.5%, respectively.

Although, as individuals, the remaining seven *MiS* features have as less impact-coverage as the *MaS* features, with the largest being 50% (E8, wave size), their total impact-coverage still reaches 62.5% (6 of 8) which is the same with the *Dyn* features. Besides, the *MiS* features have impact on fabrics' wrinkle-resistance (D4) which both the *MaS* and *Dyn* features can hardly explain.

(3) Discussions

Table 5 - 4 Major features for each fabric mechanical property

Mechanical property	*MaS* feature	*Dyn* feature	*MiS* feature
D1 (Stiff—pliable)	E21, E3, E20, E7	E24, E25, E26	
D2 (Dead—lively)	E20, E3, E7, E21	E23,	E8
D4 (wrinkle resistance)			E11, E10
D5 (stretchiness)	E20, E21, E7, E3		E8, E10 ,E2, E6, E13
D6 (Loose—tight)	E7, E21	E23, E28, E25, E26	
D10 (compressional softness)	E20, E3, E21, E7	E25	E8, E6, E2, E1
D11 (compressional springiness)	E3,E20		E8, E2

To be specific, Table 5-4 shows how these sixteen *MF*'s have impact on each fabric mechanical property. The impact levels for the seven mechanical properties are ranked in descending order and shown in Figure 5-8.

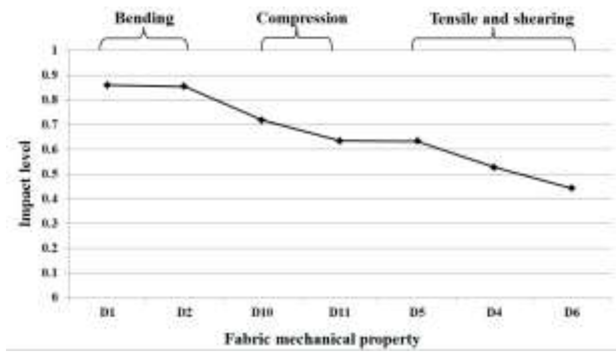


Figure 5 - 8 Impact levels for mechanical properties

Some observations are obtained from Table 5-4 and Figure 5-8.

(i) Above all, the first two mechanical descriptors (D1 and D2) concerning fabrics' bending properties are mainly affected by the *MaS* and *Dyn* features. Their impact levels are highest among all the seven mechanical properties. Moreover, as is observed from Experiment I, fabrics' bending properties can be better perceived in video scenarios than in image scenarios. These indicate that samples' dynamic effects can add much to panelists' evaluation accuracy on bending properties.

(ii) Then, for the descriptors concerning fabrics' tensile and shearing properties (D4, D5 and D6), the skirts' dynamic features do not have strong relation with D4 (wrinkle resistance) and D5 (stretchiness). Although D6 (tightness) is affected by Dyn features, its impact level is very low. Together with the results obtained from Experiment I that the GCons values on these three descriptors are relatively low in both image and video scenarios, we can assume that the dynamic features have little impact on delivering fabrics' tensile and shearing properties.

(iii) Finally, with regards to the compressional properties, D10 (compressional softness) and D11 (compressional springiness), the skirts' *MiS* and *MaS* features, especially one of the *MiS* features, E8 (wave size), have major impact. It seems that the samples' dynamic features don't have much contribution to expressing fabrics' compression properties. But according to the results in Experimental I, although the *GCons* values of these two descriptors in video scenarios are not that high as compared with those of the bending descriptors, still they are much higher than those in image scenarios. From this interesting observation, we are assuming that although the specific dynamic features are not that capable of expressing some of the fabrics' mechanical properties, the dynamic display itself is a naturally better way of representation as compared with the static one. That is to say, more mechanical information of a fabric can be discovered through dynamic displays which give a consecutive, comprehensive and vivid report about skirts' all-around features. Another similar example is found on the observation about D4 (wrinkle resistance) where the *GCons* value in video scenarios are much higher than that in image scenarios even though D4 is not affected by the *Dyn* features but the *MiS* features.

5.2.1.3 Discussions on constructional properties

Let us get back to Figure 5-5, but pay attention to the four *Constructional* properties, 'Flimsy -- firm' (D7), 'Light -- heavy' (D9), 'Non-full -- full' (D12) and 'Warm-cool' (D21), respectively.

According to the method mentioned in the previous part (Section 5.2.1.2 Eq. (5-2) and Eq. (5-3)), the *MF*'s for each property are selected and marked in brackets in Figure 5-5. It is obvious that these four properties are predominantly affected by the visual features concerning fabrics' surface attributes and thickness. To be specific, fabrics' firmness (D7) is overwhelmingly affected by their thickness (E37). Fabrics' weight (D9) is also largely correlated to their thickness, while the surface attributes such as E35 (slipperiness), E32 (bumpiness) and E29 (overall roughness) exist as second important elements. This observation is somewhat puzzling, but there is still some logic in the behind. According to our daily experience, fabrics with rough surfaces tend to give us an impression of being tightly woven with thick fibers. This can be a good proof to the so-called memory association. With regards to fabrics' fullness (D12), the most significant impact comes from their fuzziness (E34) on the surface while thickness (E37) still plays an important role therein, which is in accordance with the original definition of the fullness. Finally, the descriptor concerning fabrics' temperature on the surface (D21) are reasonably connected to fabrics' thickness (E37) and surface properties such as slipperiness (E35), overall roughness (E29) and fuzziness (E34). For example, a thick fabric with a fuzzy surface like corduroy tends to give a warm feeling as it is touched by hand while a thin satin with smooth surface would always produce a cool and refreshing hand.

5.2.1.4 Discussions on fabric color and luster

Among the thirty seven visual features, there are four descriptors concerning fabrics' color (E14, E15 and E16) and luster (E17). It is observed from this experiment (Figure 5-5 and Figure 5-6) that none of these four descriptors are taken as *RF* for any tactile property. Although E14 (color brightness) has a few impact on perceiving fabrics' weight (D9), its strength of impact is relatively low as compared with other major visual features for D9. Besides, for E15 (color vividness), E16 (color temperature) and E17 (luster), their connection with any tactile property is found to be very weak. Therefore, it is assumed that color and luster have little influence on panelists' perception of fabrics' tactile properties.

5.2.2 Study of multiple-to-single relations

In the previous section, for each tactile property, a set of major visual features (*MF*'s) are extracted by measuring the single-to-single relations between different sensory data. A sketch about the visual mechanism of fabric tactile properties is revealed. Notably, at the beginning, the thirty seven visual descriptors are selected to as comprehensively as possible depict the visible elements of a skirt. There inevitably will be some correlations between some of the descriptors which may lead to similar judgments from the panelists. These similarities are possible to exist between the *MF*'s for a tactile property. Thus, measures should be taken to discover the most critical and evident relations between fabrics' tactile properties and the visual features. As was mentioned previously, human perception is multisensory. It is assumed that the evaluation of a tactile property is obtained from the cooperation of several perceived visual features. So in this part, the principal visual features (denoted as *PF*'s) are defined as the features having the biggest cooperative impact on the corresponding tactile property.

Here, an approach, which is a further development of the previously proposed General Consistency Measure, is applied to explore the multiple-to-single relations between samples' visual features and fabric tactile properties.

5.2.2.1 Mathematical methodology

Since for each visual feature, its single-to-single relation with the corresponding tactile property consists of two coordinates, the classification consistency (denoted by *FCons*) and the ranking consistency (denoted by *RCons*), respectively, in the current method, modifications should be based on these two indices to realize the cooperation among multiple visual features.

Figure 5-9 is a general illustration of the developed mathematical approach to obtain the general consistency degree between one tactile property and multiple visual features which is named *AGCons* (Aggregated general consistency measure).

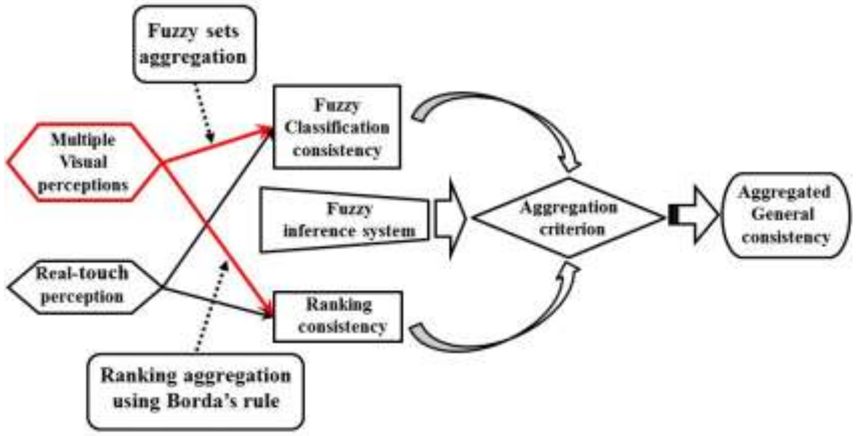


Figure 5 - 9 General illustration of developed consistency measure

(1) Modification to Classification consistency

As was illustrated previously (in Chapter 4 and Section 5.2.1), in a decision table concerning the computation of fuzzy classification consistency (*FCons*), for the single-to-single relations, both the condition set and the decision set are represented by single sensory observations. But with regards to the cases dealing with multiple-to-single relations, the condition set that represents information about skirts' visual features is an aggregated result of multiple sensory observations. The formalization of the aggregation is given below.

Imagine, we are going to measure the classification consistency of the aggregation of l visual features ($(E_1, E_2, \cdots, E_l)$) to a tactile property (which is invisible according to the definition proposed in Section 5.1.2.1 -(2) - (i). D_i , (i=1, 2, 4, 5, 6, 7, 9, 10, 11, 12, 21)). Let $U=\{e_1,\ e_2,\ \cdots,\ \ e_{18}\}$ be the set of samples. For any sample e_k , its evaluation scores on the visual features are denoted as [$c_1(e_k)$, $c_2(e_k)$,… ,$c_l(e_k)$]. $U/C=\{X_0, X_1, \cdots, X_{10}\}$ is a partition on the condition sets. According to the concept of fuzzy partitioning, $c_j(e_k)$ can be represented by a fuzzy set $E_j(e_k)=\left(\mu_{j_{X_0}}(e_k), \mu_{j_{X_1}}(e_k), \cdots, \mu_{j_{X_{10}}}(e_k)\right)$ $(j=1, 2, \cdots, l)$ with its membership function $f_{E_j}(e_k)$. Under the same partitioning principle, to aggregate different sensory variables is in fact to operate a fuzzy union between the corresponding fuzzy sets. According to the principles of fuzzy set operation [Dubois, 1996], in the current problem, the union is defined as the smallest fuzzy set containing all the l fuzzy sets to be aggregated. Let fuzzy set A be the fuzzy union result, written as $A(e_k)=E_1(e_k)\cup E_2(e_k)\cup\cdots\cup E_l(e_k)$. Its membership function is constituted as follows.

$$f_A(e_k) = \max\left\{ f_{E_1}(e_k),\ f_{E_2}(e_k), \cdots,\ f_{E_l}(e_k) \right\}, \qquad e_k \in U \tag{5-4}$$

To be precise,

$$\begin{aligned} A(e_k) &= \left\{ \mu'_{X_0}(e_k), \mu'_{X_1}(e_k), \cdots, \mu'_{X_{10}}(e_k) \right\} \\ &= \left\{ \max\left\{ \mu_{1_{X_0}}(e_k), \cdots, \mu_{l_{X_0}}(e_k) \right\}, \max\left\{ \mu_{1_{X_1}}(e_k), \cdots, \mu_{l_{X_1}}(e_k) \right\}, \cdots, \max\left\{ \mu_{1_{X_{10}}}(e_k), \mu_{l_{X_{10}}}(e_k) \right\} \right\} \end{aligned} \tag{5-5}$$

in which, the formalization of $\mu_{s_{X_i}}(e_k), \quad i = (0, 1, \cdots, 10);\ s = (1, 2, \cdots, l)$ is given below

$$\mu_{s_{X_i}}(e_k) = 1 - 0.2\left| i - c_s(e_k) \right|\ ,\ i = (0, 1, \cdots, 10);\ s = (1, 2, \cdots, l) \tag{5-6}$$

Hitherto, a fuzzy matrix $Aggr.F = \left[A(e_1), A(e_2), \cdots, A(e_{18}) \right]^T$ is obtained by conducting aggregations on all the samples. The following computation of fuzzy classification consistency is conducted between *Aggr.F* and D_i (i=1, 2, 4, 5, 6, 7, 9, 10, 11, 12, 21).

On the above basis and according to the method illustration in Section 4.2.1, the modified fuzzy classification consistency which is denoted as *AFCons* is constructed as follows.

First is the construction of aggregated fuzzy inclusion degree which is denoted as *AFinc*.

$$AFInc\left([e_k]_D / X_i \right) = \sum_{j=1}^{m} \min\left(\mu'_{X_i}(e_l), \mu_{[e_k]_D}(e_l) \right) / \sum_{j=1}^{m} \mu_{X_i}(e_l), (m = 18) \tag{5-7}$$

where X_i denotes the ith condition set and $[e_k]_D \subset U/D = \{Y_0, Y_1,\ \cdots, Y_t\}$ is the decision set where the sample e_k belongs. Here, e_k are considered to belong to $[e_k]_D$, when the following holds.

$$\mu_{[e_k]_D}(e_k) = \max\left(\mu_{Y_0}(e_k), \mu_{Y_1}(e_k), \cdots, \mu_{Y_t}(e_k) \right),\ k = (1, 2, \cdots, 18);\ t = 10 \tag{5-8}$$

Then, the fuzzy classification consistency of an equivalence class X_i of the condition part U/C with respect to the decision part U/D is modified as:

$$FCons(X_i, D) = 1 - \frac{4}{\sum_{i=0}^{t} \sum_{k=1}^{m} \mu'_{X_i}(e_k)} \sum_{k=1}^{m} AFInc\left([e_k]_D / X_i \right)\left(1 - AFInc\left([e_k]_D / X_i \right)\right),\ m = 18,\ t{=}10 \tag{5-9}$$

where, $AFInc\left([e_k]_D / X_i \right)$ is the aggregated fuzzy inclusion degree of X_i into $[e_k]_D$ for sample e_k. And we have $0 < AFCons(X_i, D) < 1$.

Finally, the classification consistency of the condition attribute C with respect to the decision attribute D can be constituted as:

$$FCons(C,D)=\sum_{i=0}^{t}\frac{\sum_{k=1}^{m}\mu'_{X_i}(e_k)}{\sum_{i=0}^{t}\sum_{k=1}^{m}\mu'_{X_i}(e_k)}AFCons(X_i,D),\left(m=6,t=10\right) \tag{5-10}$$

where, $AFInc\left([e_k]_D/X_i\right)$ is the aggregated fuzzy inclusion degree of X_i into $[e_k]_D$ for sample e_k.

(2) Modification to ranking consistency measure

In the above section, the original classification consistency has been modified to be able to aggregate the classifications of different visual variables. As another important index of our general consistency measure, in this section, the original ranking consistency is modified to aggregate the rankings of different sensory data. The basic idea comes from the Borda's rule which is originally applied to social preference problems [PEREZ, 1995]. In light of our current problem, the aggregation method is illustrated as follows.

The same example as in the above section is applied here. We are going to aggregate l visual variables $(E_1,E_2,\cdots,E_l)$. Let $U=\{e_1,\ e_2,\ \cdots,\ \ e_{18}\}$ be the set of samples. For each descriptor, we obtain a set of evaluation scores $\left[c_i(e_1),\cdots,c_i(e_{18})\right]^T$ (i=1, 2,…, l). A linear order is denoted by the sequence $\left\{e_{i_1},e_{i_2},\cdots,e_{i_{18}}\right\},\quad (i=1,2,\cdots,18)$, where for $j < k$, $c_i(e_j) > c_i(e_k)$.

A rank matrix $R = (r_{ij})$ is obtained. Here, r_{ij} is denoted by the number of sequences in which e_i is ranked in position j. According to the Borda's rule, a score of n+1-2j (here, we have n= 18) is assigned to each corresponding element in the rank matrix R. A total score s_{e_i}, summed over all the sequences, is calculated for each sample. On this basis, we obtain a new variable $Aggr.E_{a,b}=\left(s_{e_1},s_{e_2},\cdots,s_{e_{18}}\right)$ whose permutation is the aggregation result of the l visual descriptors.

Here, we give a simple example to illustrate how the aggregation works.

Imagine, we are going to aggregate the rankings of two visual variables Ea and Eb. Their experimental values on eighteen samples are listed in Table 5-5.

Table 5 - 5 Experimental values of eighteen samples on visual variables Ea and Eb (as an example)

Sample	Ea	Eb	Sample	Ea	Eb
S1	2.67	3.67	S10	2.33	2.67
S2	4.36	5.67	S11	4.38	3.33
S3	0.67	1.36	S12	1.37	0.33
S4	1.12	2.33	S13	3.86	3.50
S5	2.34	3.25	S14	4.29	4.21
S6	3.67	5.68	S15	3.71	3.21
S7	4.33	3.62	S16	6.00	6.36
S8	8.25	7.63	S17	6.10	7.00
S9	9.58	9.70	S18	6.21	7.86

First of all, we have ranked the eighteen samples according to their values on Ea and Eb in descending order, as is shown in Table 5-6.

Table 5 - 6 Ranked samples

Sample	Ea	Sample	Ea	Sample	Eb	Sample	Eb
S9	9.58	S13	3.86	S9	9.70	S7	3.62
S8	8.25	S15	3.71	S18	7.86	S13	3.50
S18	6.21	S6	3.67	S8	7.63	S11	3.33
S17	6.10	S1	2.67	S17	7.00	S5	3.25
S16	6.00	S5	2.34	S16	6.36	S15	3.21
S11	4.38	S10	2.33	S6	5.68	S10	2.67
S2	4.36	S12	1.37	S2	5.67	S4	2.33
S7	4.33	S4	1.12	S14	4.21	S3	1.36
S14	4.29	S3	0.67	S1	3.67	S12	0.33

Then, a rank matrix $R = (r_{ij})$ is obtained as follows

$R =$

a	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15	S16	S17	S18
1°	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0
2°	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1
3°	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1
4°	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0
5°	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0
6°	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0
7°	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8°	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0
9°	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
10°	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0
11°	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0
12°	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0
13°	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
14°	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0
15°	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0
16°	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0
17°	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18°	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0

In the above matrix, any element r_{ij} represents the number of times the sample e_i is ranked in the position j. For example, r_{27} signifies that the sample e_2 has been ranked as the seventh among the eighteen samples with respect to both visual variables.

Then, every element of the matrix is assigned a weight $n+1-2j$, we then have the new matrix as follows

$R =$

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15	S16	S17	S18
1°	0	0	0	0	0	0	0	0	34	0	0	0	0	0	0	0	0	0
2°	0	0	0	0	0	0	0	15	0	0	0	0	0	0	0	0	0	15
3°	0	0	0	0	0	0	0	13	0	0	0	0	0	0	0	0	0	13
4°	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	22	0
5°	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	18	0	0
6°	0	0	0	0	0	7	0	0	0	0	7	0	0	0	0	0	0	0
7°	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8°	0	0	0	0	0	0	3	0	0	0	0	0	0	3	0	0	0	0
9°	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
10°	0	0	0	0	0	0	-1	0	0	0	0	0	-1	0	0	0	0	0
11°	0	0	0	0	0	0	0	0	0	0	0	0	-3	0	-3	0	0	0
12°	0	0	0	0	0	-5	0	0	0	0	-5	0	0	0	0	0	0	0
13°	-7	0	0	0	-7	0	0	0	0	0	0	0	0	0	0	0	0	0
14°	0	0	0	0	-9	0	0	0	0	0	0	0	0	0	-9	0	0	0
15°	0	0	0	0	0	0	0	0	0	-22	0	0	0	0	0	0	0	0
16°	0	0	0	-13	0	0	0	0	0	0	0	-13	0	0	0	0	0	0
17°	0	0	-15	-15	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18°	0	0	-17	0	0	0	0	0	0	0	0	-17	0	0	0	0	0	0

Finally, we sum up the scores for each sample. Then an aggregated variable $Aggr.E_{a,b}$ whose permutation is the aggregation result of the variables Ea and Eb, is obtained and shown in Table 5-7. What is worth mentioning is that it does not matter if the new variable does not share the same dimension with the original ones, since according to the principle of Kendall's correlation coefficient, what is important is not the specific value of each sample, but its relative position in the sample set.

Table 5 - 7 Aggregated variable

Sample	E_{ab}	Sample	E_{ab}	Sample	E_{ab}
S1	-6	S7	2	S13	-4
S2	10	S8	28	S14	4
S3	-32	S9	34	S15	-12
S4	-28	S10	-22	S16	18
S5	-16	S11	2	S17	22
S6	2	S12	-30	S18	28

Subsequently, to examine the ranking consistency between the aggregated visual features and the corresponding tactile property is to compute the Kendall's ranking coefficient between $Aggr.E_{a,b}$ and D_i (i=1, 2, 4, 5, 6, 7, 9, 10, 11, 12, 21).

After the above modifications, the original General consistency measure (*GCons*) is evolved to be capable of exploring the general consistency between each tactile property and the corresponding multiple visual features. The new general consistency measure is denoted as *AGCons*.

5.2.2.2 Selection of principal visual features

In the previous study on the single-to-single relations, for each tactile property, the consistency degree (*GConc* values) of thirty seven visual features are ranked in descending order (see Figure 5-5), according to which we have obtained a set of major visual features (*MF*'s). In this part, we are going to further extract the principal visual features (*PF*'s) which are believed to have the most direct and evident impact on the corresponding tactile property. The general idea is illustrated below.

As was mentioned above, for any tactile property $D_i\ \left(i=1,2,4,5,6,7,9,10,11,12,21\right)$, we have a sequence of visual features $\left\{E(D_i)_{j_1}, E(D_i)_{j_2}, \cdots, E(D_i)_{j_1}\right\}$, $\left(j\in\{1,2,\cdots,37\}\right)$, where for $k<l$, *GCons* (E_k) >*GCons* (E_l). In this sequence, the first n visual features which individually have been proved to have major impact on D_i are taken out to constitute a smaller sequence $H_i=\left(E(D_i)_{j_1}, E(D_i)_{j_2}, \cdots, E(D_i)_{j_n}\right)$, $\left(j\in\{1,2,\cdots,37\}\right)$. In the following study, the *PF*'s are extracted from these sequences.

Then, a series of iterative computations of *AGCons* values are done on the variables in H_{i}. To be specific, the iteration starts on the *AGCons* computing of the first two visual variables. After finishing, the third variable in H_{i} is included in the computation. The number of variables being contained in a specific generation is denoted by m. The iteration will go on until m reaches n. On the basis of the results obtained from the previous single-to-single relations, this iterative computation is aimed to find the optimal cooperation of visual features to interpret a specific tactile property.

As is shown in Table 5-4, for each tactile property, the number of its *MF*'s doesn't exceed ten, so in order to reduce computational redundancy, the number of the elements contained in sequence H_{i} is determined as ten (n =10).

To find out the *PF*'s, the extractive criteria should be well defined. For any tactile property, we name the *AGCons* value of the multiple visual features after aggregation as the '*Cooperative impact level*'. In this sense, the impact level being concerned in the single-to-single relation is renamed as the '*Individual impact level*'. From a general point of view, we define that for a specific tactile property, the visual features that have the highest cooperative impact level are considered as the *PF*'s for the corresponding tactile property. For the eleven tactile properties, Figure 5-10 ((a) and (b)) shows the iterative *AGCons* results on the corresponding sequence H_i. According to the above criterion, for about half of the tactile properties, namely, D1, D2, D11, D12 and D21, their *PF*'s are defined as the variables situated before the peak of the *AGCons* line. To be specific, fabrics' stiffness (D1) is highly related to six visual features, namely, the rigidity of the silhouette (E21), the fitness at the abdomen and hip (E3), the drape of the skirt (E20), the expanding degree of the lower part of the skirt (E7), the clinging effect (E24), and the ethereality (E25). Fabrics' liveliness (D2) is expressed through three principal visual features, namely, the drape of the skirt (E20), the fitness at abdomen and hip (E3), and the expanding degree of the lower part of the skirt (E7). For the compressional springiness (D11), there are five *PF*'s, the skirt's wave size (E8), the rigidity of the pleat outline at waist (E2), the fitness at the abdomen and hip (E3), the drape of the skirt (E20), the naturalness of the pleats at abdomen and hip (E6), and the expanding degree of the lower part of the skirt (E7). Besides, for the two parametric descriptors, fullness (D12) and surface temperature (D21), the principal visual features are the same, the fuzziness (E34) and thickness of the fabric (E37) have the biggest cooperative impact on two parametric properties, fullness (D10) and perceived surface temperature (D11), respectively.

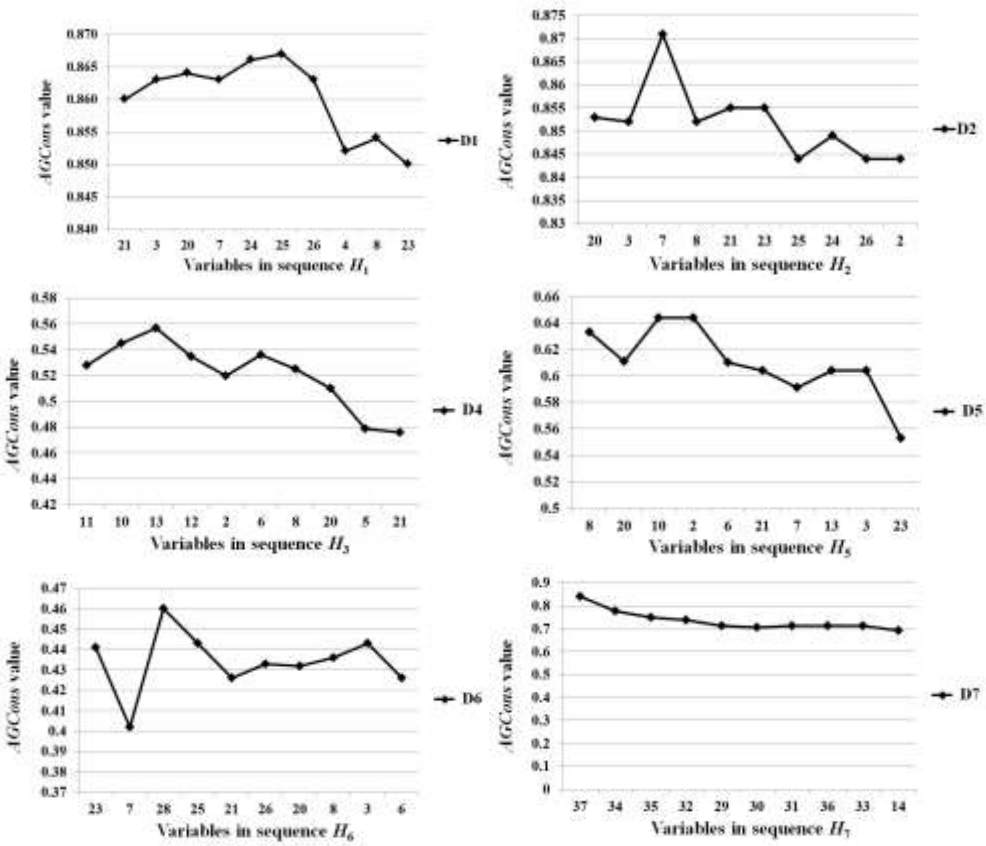


Figure 5 - 10 (a) *AGCons* values on sequence H_i for each tactile property (D1-D7)

However, for another five descriptors, D4, D5, D6, D9 and D10 respectively, to select their corresponding *PF*'s is not that easy, since there exist some singular points on their *AGCons* lines. To extract the *PF*'s is not as simple as to find the peak of the line. In fact, according to their positions on the line, these singular points can be divided into two types. The singular points of the first type are the variables with dramatically decreased *AGCons* values before the peak, including D5 (singular point: E20) and D6 (singular point: E7). Since, according to the previous study on single-to-single relations, these singular points are believed to have high individual impact on the corresponding tactile property, the decision to eliminate them should be made carefully. A pilot computing of *AGCons* is done on the rest of the variables before the peak by temporarily removing the singular point for each tactile property, which is shown in Table 5-8. After comparison, we can see that for D5, the elimination of the singular point E20 can add to its interpreting capacity, while for D6, the result is on the contrary.

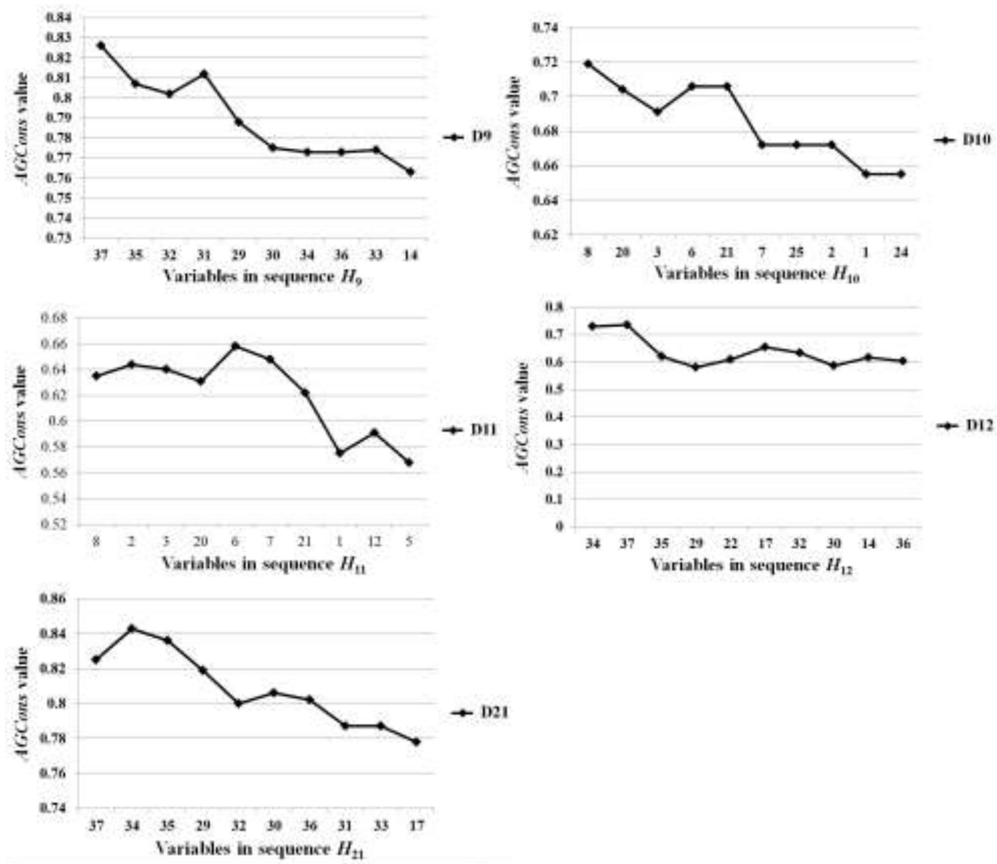


Figure 5 – 10 (b) *AGCons* values on sequence H_i for each tactile property (D9-D21)

Table 5 - 8 Cooperative impact levels before and after removing the singular points for D5 and D6

	Before	After
D5 (Stretchiness)	0.644	0.694
D6 (Tightness)	0.460	0.436

Therefore, for fabrics' stretchiness, the skirt's wave size (E8) and the wave distribution (E10) are its *PF*'s, while the three visual features, the skirt's following capacity (E23), the expanding degree of the lower part of the skirt (E7) and rhythm (E28), constitute the optimal cooperation to reveal fabrics' tightness.

Table 5 - 9 Cooperative impact levels before and after including the singular points for D4, D9 and D10

	Before	After
D4 (Wrinkle-resistance)	0.557	0.567
D9 (Weight)	0.826	0.833
D10 (Compressional softness)	0.714	0.744

The other type of singular points refer to the variables with dramatically increased *AGCons* values situated after but not far away from the peak of the line. D4, D9 and D10 are of this type. Since for each tactile property, the visual features in the sequence *H* are ranked according to their importance in a descending order, the inclusion of the features after the peak should also be done with caution. A pilot computing is conducted with the singular points included for these tactile properties. Table 5-9 shows the cooperative impact levels before and after including the singular points for D4, D9 and D10. The results show that the inclusion of the singular points will have positive impact for all the three tactile properties.

To be specific, fabrics' wrinkle-resistance (D4) is principally influence by four visual features, namely, the skirt's wave-height consistency (E11), the wave distribution (E10), the curling extent of the skirt's bottom edge (E13) and the naturalness of the pleats at abdomen and hip (E6). The panelists' perception of fabrics' weight (D9) mainly comes from their estimation on the fabric's thickness (E37) and the roughness (E31). The skirt's wave size (E8) and the naturalness of the pleats at abdomen and hip (E6) are believed to be the two principal visual features of fabrics' compressional softness (D10).

Nevertheless, there is a special tactile property, fabric firmness (D7), whose peak appears at the first point of the line, E37 (fabric thickness), but as is different from D9 and D10, its *AGCons* line after the peak reveals a stable decrease without any special point. It indicates that as the iterative computation goes on, the involvement of more visual features doesn't contribute to a better interpretation of the corresponding tactile property. Given the consistency degree of E37 (*GCons* (E37)) being relatively high (0.841), we can conclude that in a non-haptic environment, our perception about fabric firmness is highly and predominantly related to our estimation of the fabric's thickness.

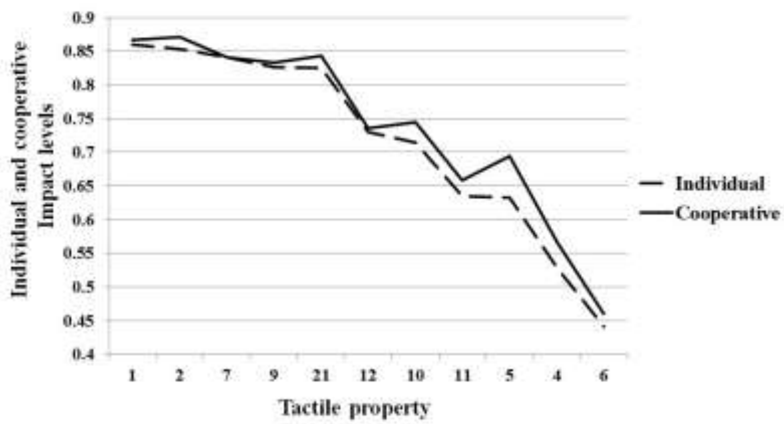


Figure 5 - 11 Impact levels before and after perceptual cooperation for each tactile property

In the previous section, for each tactile property, as is shown in Figure 5-8, its impact level is defined by the highest *GCons* value calculated from all the thirty seven visual variables. On this basis, in this part, we explored the multiple-to-single correlations between the visual features and the corresponding tactile properties. Figure 5-11 shows the comparison between the individual impact level (represented in dash line) and the impact level obtained from the cooperation of extracted principal visual features (represented in solid line) for each tactile property. It is evident that after perceptual cooperation, the impact level is increased for every tactile property (except for D7 (firmness), no increase nor decrease is detected). It's proved that in a non-haptic environment, our evaluation of fabrics' tactile properties results from the cooperation of multiple visual perceptions, and there exist a few principal visual features whose cooperation can make the biggest contribution to the interpretation of each tactile property. After the computation, seventeen out of the overall thirty seven visual features remain to have significant impact on the perception of the eleven fabric tactile properties, which is significant for carrying out more targeted studies on fabric hand in the future with the complexity of the problem greatly reduced.

5.3 Predictive modeling based on a fuzzy neural network (ANFIS)

In the previous part of the study, several *PF*'s (principal visual features) are extracted and proved to have the most significant cooperative impact on each tactile property. On this basis, here, we are going to establish a predictive model to quantify these multiple-to-single relationships. Given that we have a relatively small number of samples, and there exists much uncertainty and imprecision in sensory data, an adaptive network-based fuzzy inference system (ANFIS) is employed to solve the current modeling problem. [JANG, 1993]

This system has absorbed the advantages of both neural network and fuzzy inference system. By setting up intuitively reasonable initial membership functions, a learning process is launched to generate a set of fuzzy if-then rules to describe the input-output behavior of the data system. By employing ANFIS, the complicated relations between different sensory data can be modeled with reliability and interpretability.

5.3.1 Data description

The basic structure and principles of ANFIS has been introduced in detail in Section 3.4. Thus, we will not make redundant illustrations in this section.

According to the study in the previous section, the eighteen samples are characterized by eleven tactile properties (i.e., invisible properties). To be specific, for each tactile property, a set of principal visual features are extracted using our proposed approach. In this part of the study, for each pair of multiple-to-single relationship, an inputs-output model, which is called ANFIS, is developed.

In practice, the eighteen samples are taken as the training data for the model. Three additional samples which were selected and prepared in the same way as the eighteen samples are included as the testing data to verify the modeling performance.

Let us take the tactile descriptor pair 'dead--lively' (D2) as an example. Its experimental value is regarded as the output of the ANFIS model, while the corresponding *PF*'s, i.e., E20, E3 and E7 respectively, are taken as the inputs.

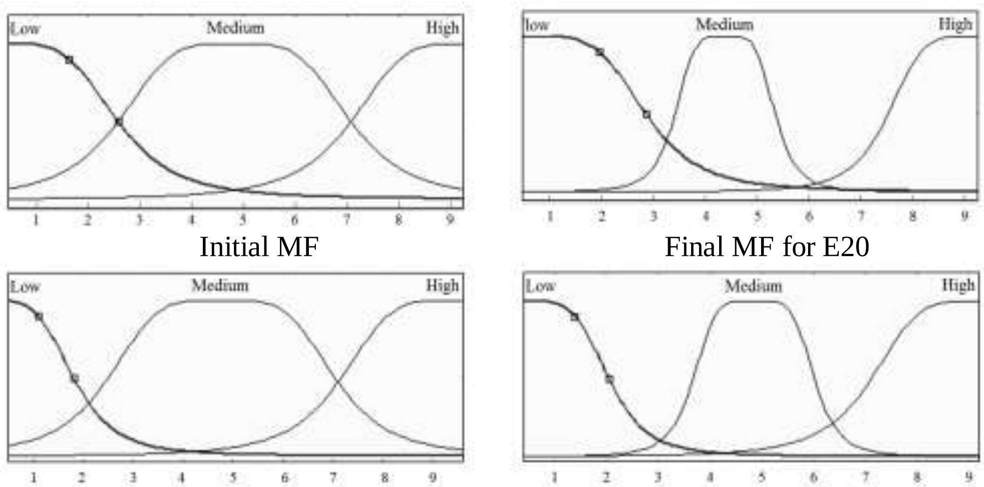
5.3.2 Development of ANFIS

In an ANFIS model, it is crucial to decide the type and the number of the membership functions for each input variable. As a normal choice for representing fuzzy data, the bell-shaped membership function is employed in our study. Generally, the more the membership functions are, the more precise the inference will be. But the increase of the number of membership functions can also result in computational redundancy in the system. As regards to our current problem, for different tactile properties, the number of the principal visual features is different. A counterbalance should be made between the number of the *PF*'s and the number of corresponding membership function. It is decided that for the tactile variables who have more than two (not including two) *PF*'s, they are assigned three membership functions for each input; for the tactile variables who have two *PF*'s, five membership functions are applied; and for the fabric firmness (D7) who has only one *PF*, seven membership functions are required for making a relatively reliable inference. Thus, for 'dead—lively' (D2), three membership functions are assigned to each input of the model. Correspondingly, twenty seven if-then rules will be learned in the ANFIS system.

5.3.3 Modeling results

Figure 5-12 shows the plots of the membership functions before and after training of the model. As is shown in the figure, significant modifications have been done to the shapes of the initial membership functions (the same for all the three inputs) through the learning process.

Compared with the ordinary ANN (Artificial Neural Network), the FNN (Fuzzy-neural Network) applied in this study has high capacity in both parametric learning and result reasoning. By calculating the optimal parametric values of the membership functions, a set of explanatory rules are extracted from the implicit and ambiguous relations lying between the input and output data. In our study, after the training of the model, a total of twenty seven if-then rules have been extracted for D2. For the rest of the tactile properties, analogous processing is applied to extract reasoning rules. For each tactile property, two rules are selected and listed in Table 5-10.



Initial MF

Final MF for E20

Final MF for E3

Final MF for E7

Figure 5 - 12 Membership functions before and after training for each input

Thus, the ANFIS model required in this study has been established, according to which the value of any tactile property of a fabric can be mathematically predicted from its principal visual features.

Table 5 - 10 Examples of if-then rules for each tactile property

D#	Rule N.	Rule description
D1	R49	if (E21 is low)and (E3 is medium)and (E20 is low)and (E7 is low) and (E24 is low)and (E25 is low), then D1= 0.05488*E21+0.1255*E3+0.153*E20+0.1035*E7+0.1361*E24+0.1303*E25+0.09896
	R82	if (E21 is medium)and (E3 is high)and (E20 is medium)and (E7 is medium) and (E24 is high)and (E25 is medium), then D1= 0.09759 *E21+0.09516 *E3+0.1058 *E20+0.08852*E7+0.1022*E24+0.09895*E25+0.01451
D2	R2	if (E20 is low)and(E3 is low)and(E7 is medium),then D2=0.6532*E20+0.3938*E3+0.6362*E7+0.1997
	R10	if (E20 is medium)and(E3 is low)and(E7 is low),then D2=0.4918*E20+0.3418*E3+0.4515*E7+0.1586
D4	R14	if (E11 is low)and(E10 is medium)and(E13 is medium)and(E6 is medium),then D3=0.1089*E11+0.1897*E10+0.1129*E13+0.2759*E6
	R46	if (E11 is low)and(E10 is medium)and(E13 is medium)and(E6 is medium),then D3=0.864*E11+0.8523*E10+0.166*E13+0.2817*E6+0.1273
D5	R4	if (E8 is very low)and(E10 is high), then D4=0.4474*E8+0.9337*E10+0.1488
	R18	if (E8 is high)and(E10 is medium), then D4=0.4372*E8+0.4014*E10+0.06838
D6	R2	if (E23 is low)and(E7 is low)and(E28 is high),then D5=0.1596*E23+0.1704*E7+0.1102*E28+0.02242

	R23	if (E23 is high)and(E7 is medium)and(E28 is medium),then D5=0.1786*E23+0.1453*E7+0.1281*E28+0.02206
D7	R2	if (E37 is quite low), then D6=3.198 *E37+1.601
	R6	if (E37 is quite high), then D6=-1.687 *E37+16.33
D9	R8	if (E37 is medium)and(E31 is high),then D7=0.6362*E37+0.9206*E31+0.1932
	R24	if (E37 is very high)and(E31 is high),then D7=0.2542*E37-0.05325*E31-0.005743
D10	R9	if (E8 is low)and(E6 is high), then D8=0.131*E8+0.08286*E6+0.03077
	R17	if (E8 is high)and(E6 is low), then D8=0.4356*E8+0.2699*E6+0.07846
D11	R29	if (E8 is low)and(E2 is medium)and(E3 is low)and(E20 is low)and(E6 is medium),then D9=0.0383*E8-0.05971*E2+0.02833*E3+0.02947*E20+0.04268*E6-0.01258
	R153	if (E8 is medium)and(E2 is high)and(E3 is medium)and(E20 is high)and(E6 is high),then D9=0.1231*E8-0.1743*E2+0.1646*E3+0.172*E20+0.1765*E6-0.02441
D12	R11	if (E34 is medium)and(E37 is very low),then D10=0.06658*E34+0.04071+0.02466
	R19	if (E34 is high)and(E37 is high),then D10=0.4122*E34-0.3065*E37+0.07575
D21	R8	if (E37 is low)and(E34 is medium), then D11=0.4988*E37+0.235*E34+0.03215
	R24	if (E37 is very high)and(E34 is high),then D11=0.1098*E37+1.017*E34-0.04374

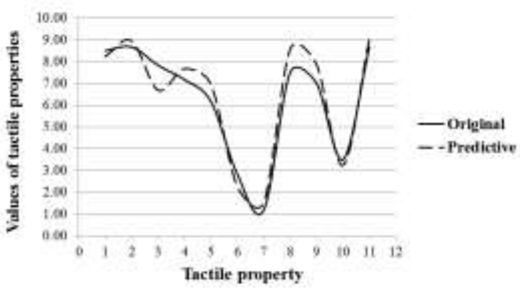
5.3.4 Verification of modelling performance

The same sensory experiments (real-touch and visual scenarios) were carried out on the three testing samples. Two sets of sensory data having been obtained to describe both the principal visual features and the fabric tactile properties of the skirts are taken as the inputs of the model and the so-called original results with which the predictive results are to be compared. A set of eleven predictive results corresponding to the eleven fabric tactile properties are produced by the model for each testing sample (denoted as TS#).

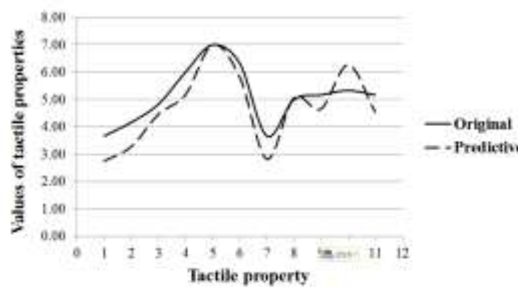
Table 5-11 lists the original, predictive values of the testing samples as well as the computed error. For better illustration, Figure 5-13 shows the comparison on the eleven fabric tactile properties for each testing sample. In this figure, original values are depicted in dash lines and the estimated perceptions are represented in solid lines. According to the closeness of the two lines in each plot, we can believe that the established model has a good predictive capacity. Besides, the calculated predictive errors over most of the tactile properties for each testing sample don't exceed 1.0, which is regarded as a relatively satisfactory result in sensory science for which the so-called accurate estimation is of no significance. Therefore, it is concluded that, as far as is concerned in this study, the developed ANFIS model is capable of well predicting fabrics' tactile properties from the perceived visual features of the samples. So far, the visual interpretative mechanism of fabrics' tactile properties is successfully unveiled.

Table 5 - 11 Comparison of original and predictive values of testing samples

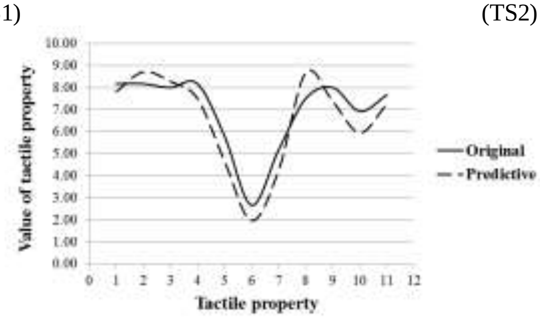
	TS1			TS2			TS3		
	Original	Predictive	Error	Original	Predictive	Error	Original	Predictive	Error
D1	8.50	8.23	0.27	3.67	2.75	0.92	8.17	7.82	0.35
D2	8.67	8.95	0.28	4.17	3.28	0.88	8.17	8.71	0.54
D3	7.83	6.68	1.15	4.83	4.46	0.37	8.00	8.28	0.28
D4	7.17	7.67	0.50	6.00	5.18	0.82	8.17	7.50	0.67
D5	6.17	6.95	0.78	7.00	7.00	0.00	5.80	4.66	1.14
D6	2.83	2.27	0.56	6.33	5.82	0.51	2.66	1.96	0.70
D7	1.17	1.52	0.35	3.67	2.83	0.83	5.17	4.24	0.92
D8	7.50	8.57	1.07	5.00	5.06	0.06	7.50	8.68	1.18
D9	7.00	7.86	0.86	5.17	4.66	0.51	8.00	7.37	0.63
D10	3.50	3.24	0.26	5.33	6.27	0.94	6.92	5.95	0.97
D11	8.67	9.06	0.39	5.17	4.55	0.62	7.67	7.25	0.42



(TS1)



(TS2)



(TS3)

Figure 5 - 13 Comparison between original and predictive results on tactile properties for testing samples

5.4 Conclusion

In the previous chapter (Chapter 4), it has been proved that fabrics' tactile properties can be perceived through products' visual representations. On this basis, the current study has been aimed to further investigate how this visual interpretation works. Two sensory experiments (Experiment II) have been carried out on eighteen flared skirts (in which twelve samples are newly involved in the current experiments) to obtain the samples' tactile properties and visual features respectively.

Two major steps have been designed to unveil the visual interpretative mechanism. The first step is to discover the relationships between fabric tactile properties and visual features, which can be called the depiction of mechanism. This task has been realized by extracting principal visual features for fabric tactile properties. Initially, the approach which was proposed in Chapter 4 has been applied here to measure the single-to-single relations of the two sensory data, from which a set of major visual features are selected. Then, this approach has been modified to be able to measure the multiple-to-single relations concerned in the multisensory cooperation during the evaluation of fabrics' tactile properties in a non-haptic environment. Here, the multisensory cooperation takes the meaning of the involvement of more than two visual features to express one specific tactile property in a non-haptic environment.

On the above basis, the second step of the current study is to quantify the explored mechanism. An inputs- output model between each tactile property and the corresponding principal visual features has been established using an adaptive network-based fuzzy inference system (ANFIS) whose strength lies in its high capacity of learning while interpreting relations of high uncertainty and imprecision. Finally, by introducing three testing samples, this model has been verified to be capable of predicting fabrics' tactile properties from the perceived visual features with a satisfactory accuracy.

GENERAL CONCLUSION AND PROSPECT

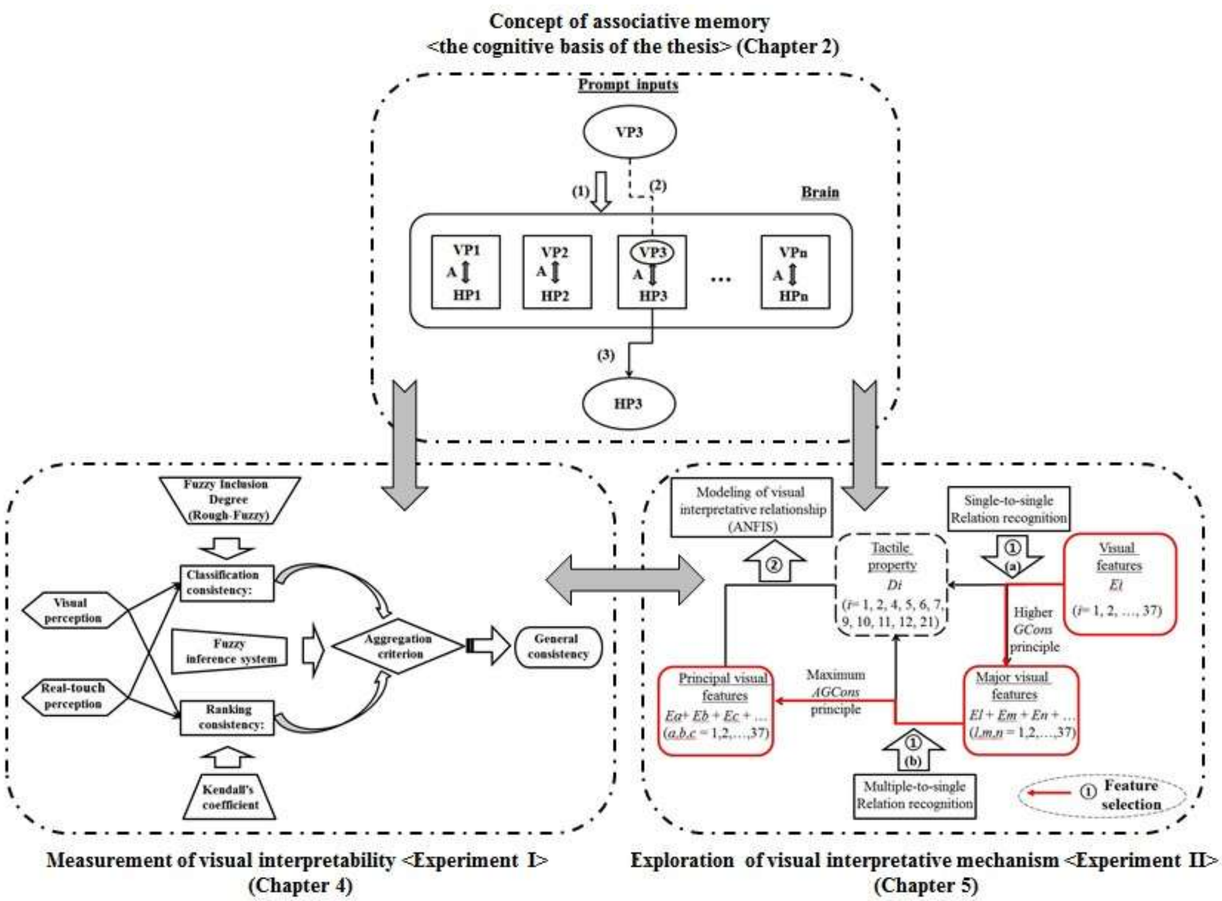


Figure 6 - 1 General scheme of the study

Nowadays, as internet has been developed to be ever more considerate and interesting, online shopping has emerged as a compelling way of consumption that everyone would love to have a try. However, on internet, the products' intangibility is a big barrier preventing the manufacturers from providing their services in the most satisfactory way, which is especially the case in the textile industry where to be able to touch, is customers' basic request during purchasing. So far, much effort has been dedicated to providing our consumers with the most close-to-real sense of fabric hand through virtual experiences, among which the most remarkable progress maybe the invention of many force feed-back devices. But till now, there is not such a device that can provide a satisfactory simulation of real fabric touch. And the mechanical principles on which these devices are based determine from the deep nature that they would not lead to exact interpretation of the complex and somewhat mysterious human perception from which the fabric hand is defined.

It is known that up to 80% of the daily information is perceived by our eyes. Vision is believed to be the most widely used and reliable sensory channel for information acquisition. Moreover, as compared with touch, vision can be obstacle – free on internet. On the above grounds, in the current thesis, we propose, for the first time, to study fabrics' tactile properties from the angle of visual perception.

The general scheme of our research is shown in the above figure.

In Chapter 2, the feasibility of visual interpretation of tactile information has been discussed from the perspectives of physiological psychology and cognitive psychology. In real life, our intuition tells us that the various properties of an object is recognized in different ways by the senses, yet reflect the common source. To be specific, what is felt is always combined with what is seen. Vision and haptics work together to create a rich and cross-modal representation of an object, which is called multisensory perception. It is not an exception for the multisensory perception of fabric tactile properties. According to the type of substance to be evaluated, fabric tactile properties have been classified to two major categories. One category consists of properties concerning fabrics' surface characteristics, or texture according to the more standardized psychological terminology. For these properties, although they are intuitively thought of as haptic, many researches tend to have consensus on the fact that there is no strict hierarchy to any of the senses (i.e., touch or vision) during multisensory perception. The perceptual accuracy of fabric textures is almost equal for touch and vision. The other category involves properties mainly concerning fabrics' mechanical features, or they can be called non-texture properties. For these properties, visual perception is not that normal or easy as for the textures, but it is not impossible. According to studies on cognitive memory, visual perception is based on the mechanism called associative memory which has been illustrated using a cognitive machine, in which the sensory inputs about an external stimulus is perceived through different pathways but stored in a single memory folder. When any content of the folder is retrieved, all the sensory information in this folder will be obtained at the same time. This provides grounds for the hypothesis that when certain external stimuli are absent, it is still possible to perceive the appropriate properties through the available senses, as long as adequate memory association has been accumulated between the absent senses and the remaining ones during previous multisensory experience. Therefore, with regards to the problem of our study, there are plenty of reasons to suppose that fabric tactile properties can be to some extent (probably big extent) perceived through the visual representations of the textile products, which serves as the theoretical foundation of our study.

On the basis of the discussions in Chapter 2, in Chapter 4 we attempted to verify the proposed hypothesis through our own research. Here, we have designed and carried out a series of sensory experiments on a number of typical textile fabrics (Experiment I). During the experiments, the textile fabrics were made into flared skirts as our experimental samples to be evaluated in video, image and real-touch scenarios by a panel of textile experts. A novel mathematical approach based on the ideas of rough sets and fuzzy sets theories has been proposed to measure the consistency of visual perceptions (being either video or image ones) to real-touch perceptions of the samples' tactile properties. After being compared with the conventional linear correlation method, this approach is believed to be capable of detecting nonlinear patterns lying beneath sensory data while being safe to use a comparatively small number of experimental samples as is the case in the current study. In this research, we have obtained two principal conclusions which are of great significance for the entire study. One is that most tactile properties of a textile product (especially for the properties concerning fabric surface characteristics and material recognition) can be perceived to a big extent through specific visual representations, which has confirmed the hypothesis proposed in Chapter 2. The other is that generally speaking video representations can provide more concrete and accurate information than image representations, while there are some exceptions where image observation can lead to better performance. For example, besides that panelists tended to perform slightly better in video scenarios than in image scenarios under the circumstance that the interpretability of both representations is already quite high, most of fabrics' mechanical properties such as bending and compressive properties can be better perceived through video representations. But for some basic properties such as thickness and tightness, generally better performance has been detected in image evaluations where more careful observation is required. This finding have helped to determine that in the following research, in order to offer as much visual information as possible both video and image representations should be made available to the panelists during evaluations.

In previous chapter, the visual interpretability with respect to fabric tactile properties has been proved. On this basis, finally, Chapter 5 is aimed to further investigate the interpretative mechanism of fabric tactile perception through visual representations. A new set of textile fabrics which have been made into flared skirts of the same specifications as the previous samples in Experiment I are involved in this part of the study (Experiment II). Visual representations including video clips and multi-angle photos were created also in the same way for each new sample. Two sensory tests have been carried out on a total of eighteen samples including six initial and twelve new ones. One test is about the evaluation of samples' tactile properties in real-touch circumstance. Since the six initial samples have already been evaluated in Experiment I, in this part of the study, some standardized procedures have been designed which is aimed to keep all the eighteen samples in the same evaluation system. The other test is aimed to evaluate samples' visual features. With regards to data analysis, two steps are to be taken to investigate the visual interpretative mechanism. In the first step, the mathematical approach proposed in Chapter 4 has been modified to be able to measure the multiple-to-single relations of each tactile property with several visual features so as to extract principle visual features which claim most evident impact on revealing the corresponding fabric tactile property. On this basis, the next step is to further quantify the discovered interpretative relationships between each tactile property and its principal visual features. To achieve this, a fuzzy neural network, i.e., ANFIS, has been proposed as the modeling method. This method is especially competent in solving the sensory problem to be concerned in the current study due to the fact that it can, on the basis of a high capacity in data learning, recognize complex non-linear relations in sensory data, while give straightforward interpretation of modeling results by extracting fuzzy rules. After modeling, the multiple-to-single relationships of tactile properties with corresponding principal visual features are quantified. With this predictive model, it is possible to forecast any tactile property by evaluating a small number of visual features of the samples.

Due to the time limit, the current work is still far from being perfect. In future research, more effort should be dedicated to the following perspectives.

(1) The number of samples involved in the present study is quite limited and the conclusions are drawn upon one specific type of textile product. But as we all know, reliable analysis results are relevant, to a significant extent, to a big and comprehensive experimental sample set.

Therefore, in the future, in order to obtain more generalized and concrete conclusions about the visual-tactile relations, it is imperative to involve more types of samples with more diverse tactile properties into the evaluation system.

(2) For sensory evaluation, the establishment of semantic space about the target product is no doubt of primary importance. In the current study, the selection of linguistic descriptors is targeted to one special type of textile product which is a big limitation for the sensory approach to be generalized to a wider range of applications. So, the future work would be to develop a more systematic and normalized semantic space in a comprehensive evaluation system so as to provide the biggest possibility in characterizing different types of textile products.

(3) The current work represents a first and significant step forward on the way of investigating the possibility of creating effective and efficient interaction between fabric tactile properties and corresponding visual representations so as to provide our consumers with the most close-to-real sense of fabric in a non-haptic virtual environment. A lot of effort should be done to let our knowledge and techniques reach out to the consumers. It is previewed that, by integrating interactive technologies into our methodology, in the future, we will be able to build a virtual system, in which all the desired information about a textile product is illustrated in virtualized forms including the visualized tactile properties. By then, people's purchasing experience would be greatly enriched.

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My special thanks go to the individuals who have been willing to spend their precious time in participating in my time-consuming experiments. Some of them are from ENSAIT, respectively, the researchers and teachers, Dr. Pascal BRUNIAUX, Dr. Christine CAMPAGNE, Dr. Anne PERWUELZ, Dr. Agnieszka CICHOCKA, and Miss Sandrine PESNEL; PhD colleagues, Vanessa PASQUET, Ludivine MEUNIER, Munir ASHRAF, Gaurav AGARWAL, Nizar

DIDANE, Songxue SHA and Lichuan WANG; engineering students, Haoyu GONG, Xiaoxu ZHANG, Hong ZHU, Dakun LIU, Jingwei DU, Yi LI, Peijun XU, Lei XU, Nan JIANG, Panpan QIN, Shuo YANG, Rui MIN, and Qi GUO, et al. Some of them are from colleagues from HEI, namely, Dr. Julie BOULENGUEZ, Gildas MORVAN, Chiraz AMMAR and Alexandre VEREMME, et al.

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My big gratitude goes to my colleagues and close friends for their invaluable support and encouragement which accompanied me all the time during my stay in France. They are Stojangka PETRUSIC, Xiaoguang DENG, Yijun ZHU, Xiao CHEN, Junyao ZHANG, Awa DOUMBIA SOROFE, Marion AMOIT, Gwladys BENISTANT, Xuyuan TAO, Zoran TIGANJ, Milan ELDELJ, Jovan RODAK, Yu FU, Yi YU, Juanrong HUANG, et al. Thank you for being with me.

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Appendix : Questionnaires for sensory evaluations

(1) **Experiment I** (Fabric hand evaluation on 6 samples in real-touch, video and image scenarios)

FABRIC HAND EVALUATION

NAME:		SEX:	F□ H□	AGE:		DOMAIN:	

SCALE: Échelle					
De 0 à 10 :					
Extremely	Very	Quite	Fairly	More than medium	Medium
Extrêmement	Très	Vraiment	Assez	Plus que moyennement	Moyennement
0	**1**	**2**	**3**	**4**	**5**
More than medium	Fairly	Quite	Very	Extremely	
Plus que moyennement	Assez	Vraiment	Très	Extrême-ment	
6	**7**	**8**	**9**	**10**	

Fabric tactile properties													
1	**Stiff : Rigide**	0	1	2	3	4	5	6	7	8	9	10	**Pliable: Souple**
①	②	③					④					⑤	⑥
2	**Dead: Mort/intangible**	0	1	2	3	4	5	6	7	8	9	10	**Lively: vif**
①	②	③					④					⑤	⑥
3	**Non-draped: Non tombant**	0	1	2	3	4	5	6	7	8	9	10	**Draped: Tombant**
①	②	③					④					⑤	⑥
4	**Crumply: Froissable**	0	1	2	3	4	5	6	7	8	9	10	**Wrinkle-resistant: Infroissable**
①	②	③					④					⑤	⑥
5	**Non-stretchy : Non élastique**	0	1	2	3	4	5	6	7	8	9	10	**Stretchy: Elasitique**
①	②	③					④					⑤	⑥
6	**Loose: Lâche**	0	1	2	3	4	5	6	7	8	9	10	**Tight: Serré**
①	②	③					④					⑤	⑥
7	**Flimsy: Fragile/peu solide**	0	1	2	3	4	5	6	7	8	9	10	**Firm: Ferme**
①	②	③					④					⑤	⑥

8	**Thin: Mince**	0	1	2	3	4	5	6	7	8	9	10	**Thick: Epais**
①	②	③					④					⑤	⑥
9	**Light: Léger**	0	1	2	3	4	5	6	7	8	9	10	**Heavy: Lourd**
①	②	③					④					⑤	⑥
10	**Hard : dur**	0	1	2	3	4	5	6	7	8	9	10	**Soft (compression) : Doux (en compression)**
①	②	③					④					⑤	⑥
11	**Non-springy (in compression) Non élastique (en compression)**	0	1	2	3	4	5	6	7	8	9	10	**Springy (in compression) : Elastique (en compression)**
①	②	③					④					⑤	⑥
12	**Non-full : Non-riche**	0	1	2	3	4	5	6	7	8	9	10	**Full: Riche**
①	②	③					④					⑤	⑥
13	**Rough (overall surface): Rugueux (surface entière)**	0	1	2	3	4	5	6	7	8	9	10	**Smooth (overall surface): Lisse (surface entière)**
①	②	③					④					⑤	⑥
14	**Grainy: Granuleux**	0	1	2	3	4	5	6	7	8	9	10	**Non grainy : Non granuleux**
①	②	③					④					⑤	⑥
15	**With ridges: Stries**	0	1	2	3	4	5	6	7	8	9	10	**Without ridges : Sans stries**
①	②	③					④					⑤	⑥
16	**Bumpy: Accidenté**	0	1	2	3	4	5	6	7	8	9	10	**Non bumpy : Non accidenté**
①	②	③					④					⑤	⑥
17	**Prickly: Epineux**	0	1	2	3	4	5	6	7	8	9	10	**Non prickly : Non épineux**
①	②	③					④					⑤	⑥
18	**Fuzzy(downy): Duveteux**	0	1	2	3	4	5	6	7	8	9	10	**Non fuzzy : Non duveteux**
①	②	③					④					⑤	⑥
19	**Non-sllippery : Non-glissant**	0	1	2	3	4	5	6	7	8	9	10	**Slippery: Glissant**
①	②	③					④					⑤	⑥
20	**Harsh: Rêche**	0	1	2	3	4	5	6	7	8	9	10	**Soft (surface): Doux (surface)**
①	②	③					④					⑤	⑥
21	**Warm: Chaud**	0	1	2	3	4	5	6	7	8	9	10	**Cool: Frais**
①	②	③					④					⑤	⑥

SCALE：Échelle					
De 0 à 10 :					
Not at all	Very little	A little	More than a little	Less than medium	Medium
Pas du tout	Très peu	Un peu	Plus qu’un peu	Moins que moyennement	Moyennement
0	**1**	**2**	**3**	**4**	**5**
More than medium	Fairly	Quite	Very	Extremely	
Plus que moyennement	Assez	Vraiment	Très	Extrêmement	
6	**7**	**8**	**9**	**10**	

TEXTURE-LIKE, Texture similaire												
22	**Cotton-like**：Comme le coton	0	1	2	3	4	5	6	7	8	9	10
①	②	③	④	⑤	⑥							
23	**Silk-like**：Comme la soie	0	1	2	3	4	5	6	7	8	9	10
①	②	③	④	⑤	⑥							
24	**Linen-like**：Comme le lin	0	1	2	3	4	5	6	7	8	9	10
①	②	③	④	⑤	⑥							
25	**Synthetic-like**：Comme la fibre synthétique	0	1	2	3	4	5	6	7	8	9	10
①	②	③	④	⑤	⑥							

(2) **Experiment II** (sensory evaluations on 12 new samples in real-touch scenarios)

- **Experiment II (a)** (Tactile evaluation in real-touch scenarios)

<u>QUESTIONNAIRES:</u>

FABRIC HAND EVALUATION

NAME:		SEX:	F□ H□	AGE:		DOMAIN:	

SCALE: Échelle					
De 0 à 10 :					
Extremely	Very	Quite	Fairly	More than medium	Medium
Extrêmement	Très	Vraiment	Assez	Plus que moyennement	Moyennement
0	**1**	**2**	**3**	**4**	**5**
More than medium	Fairly	Quite	Very	Extremely	
Plus que moyennement	Assez	Vraiment	Très	Extrême-ment	
6	**7**	**8**	**9**	**10**	

Fabric tactile properties						**Fabric tactile properties**					
1	**Stiff : Rigide –Pliable : Souple**					**12**	**Non-full : Non-riche -- Full: Riche**				
①	②	③	④	⑤	⑥	①	②	③	④	⑤	⑥
⑦	⑧	⑨	⑩	⑪	⑫	⑦	⑧	⑨	⑩	⑪	⑫
2	**Dead: Mort/intangible – Lively : vif**					**13**	**Rough: Rugueux (surface entière) – Smooth : Lisse (surface entière)**				
①	②	③	④	⑤	⑥	①	②	③	④	⑤	⑥
⑦	⑧	⑨	⑩	⑪	⑫	⑦	⑧	⑨	⑩	⑪	⑫
3	**Non-draped: Non tombant – Draped : Tombant**					**14**	**Grainy: Granuleux -- Non grainy : Non granuleux**				
①	②	③	④	⑤	⑥	①	②	③	④	⑤	⑥
⑦	⑧	⑨	⑩	⑪	⑫	⑦	⑧	⑨	⑩	⑪	⑫
4	**Crumply: Froissable--Wrinkle-resistant: Infroissable**					**15**	**With ridges: Stries -- Without ridges : Sans stries**				
①	②	③	④	⑤	⑥	①	②	③	④	⑤	⑥
⑦	⑧	⑨	⑩	⑪	⑫	⑦	⑧	⑨	⑩	⑪	⑫
5	**Non-stretchy : Non élastique -- Stretchy: Elasitique**					**16**	**Bumpy: Accidenté -- Non bumpy : Non accidenté**				
①	②	③	④	⑤	⑥	①	②	③	④	⑤	⑥
⑦	⑧	⑨	⑩	⑪	⑫	⑦	⑧	⑨	⑩	⑪	⑫
6	**Loose: Lâche -- Tight: Serré**					**17**	**Prickly: Epineux -- Non prickly : Non épineux**				

①	②	③	④	⑤	⑥
⑦	⑧	⑨	⑩	⑪	⑫
7	**Flimsy: Fragile/peu solide -- Firm: Ferme**				
①	②	③	④	⑤	⑥
⑦	⑧	⑨	⑩	⑪	⑫
8	**Thin: Mince -- Thick: Epais**				
①	②	③	④	⑤	⑥
⑦	⑧	⑨	⑩	⑪	⑫
9	**Light: Léger -- Heavy: Lourd**				
①	②	③	④	⑤	⑥
⑦	⑧	⑨	⑩	⑪	⑫
10	**Hard : dur -- Soft(compression): Doux**				
①	②	③	④	⑤	⑥
⑦	⑧	⑨	⑩	⑪	⑫
11	**Non-springy (in compression) Non élastique – Springy: Elastique (en compression)**				
①	②	③	④	⑤	⑥
⑦	⑧	⑨	⑩	⑪	⑫

①	②	③	④	⑤	⑥
⑦	⑧	⑨	⑩	⑪	⑫
18	**Fuzzy(downy):Duveteux --Non fuzzy :Non duveteux**				
①	②	③	④	⑤	⑥
⑦	⑧	⑨	⑩	⑪	⑫
19	**Non-sllippery : Non-glissant -- Slippery: Glissant**				
①	②	③	④	⑤	⑥
⑦	⑧	⑨	⑩	⑪	⑫
20	**Harsh: Rêche -- Soft (surface): Doux (surface)**				
①	②	③	④	⑤	⑥
⑦	⑧	⑨	⑩	⑪	⑫
21	**Warm: Chaud -- Cool: Frais**				
①	②	③	④	⑤	⑥
⑦	⑧	⑨	⑩	⑪	⑫

SCALE： Échelle					
De 0 à 10 :					
Not at all	Very little	A little	More than a little	Less than medium	Medium
Pas du tout	Très peu	Un peu	Plus qu’un peu	Moins que moyennement	Moyennement
0	**1**	**2**	**3**	**4**	**5**
More than medium	Fairly	Quite	Very	Extremely	
Plus que moyennement	Assez	Vraiment	Très	Extrêmement	
6	**7**	**8**	**9**	**10**	

TEXTURE-LIKE, Texture similaire												
22	**Cotton-like：Comme le coton**	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
①	②	③	④	⑤	⑥							
⑦	⑧	⑨	⑩	⑪	⑫							
23	**Silk-like：Comme la soie**	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
①	②	③	④	⑤	⑥							
⑦	⑧	⑨	⑩	⑪	⑫							

<table>
<tr><td>24</td><td>Linen-like：Comme le lin</td><td>0</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>6</td><td>7</td><td>8</td><td>9</td><td>10</td></tr>
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<tr><td>25</td><td>Synthetic-like：
Comme la fibre synthétique</td><td>0</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>6</td><td>7</td><td>8</td><td>9</td><td>10</td></tr>
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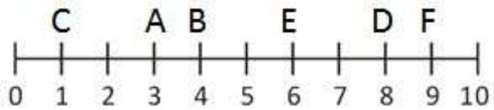
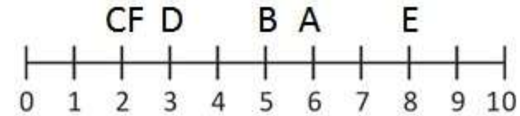
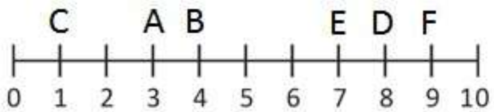
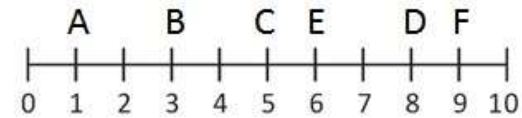
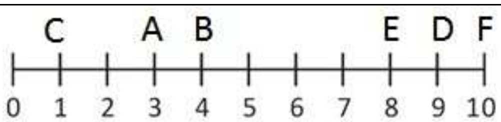
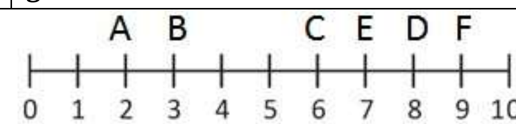
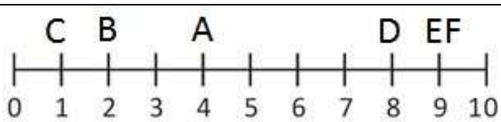
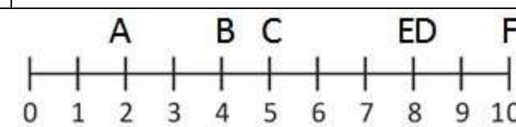
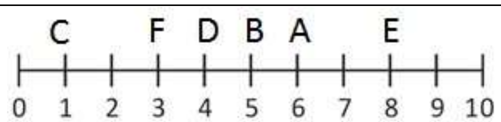
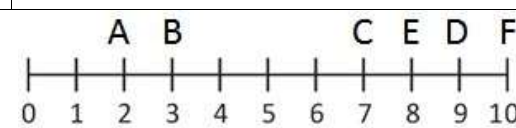
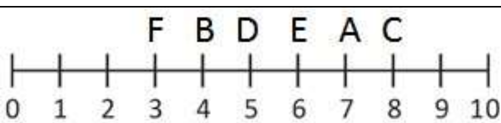
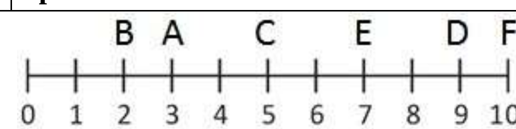
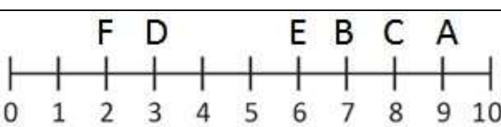
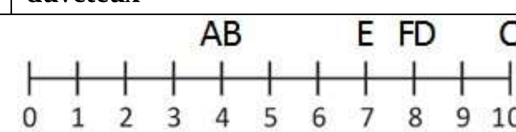
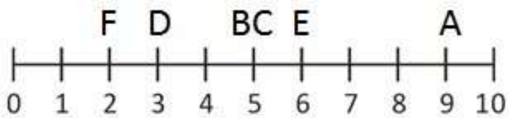
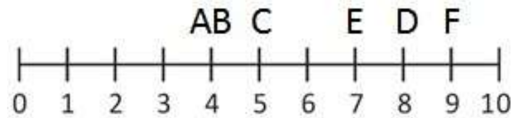
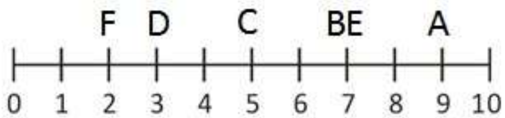
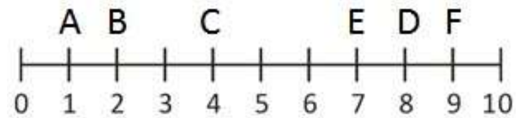
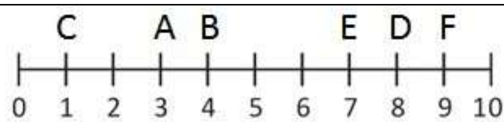
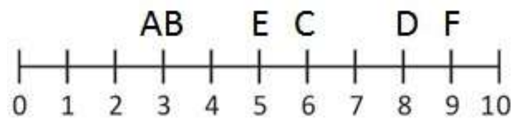
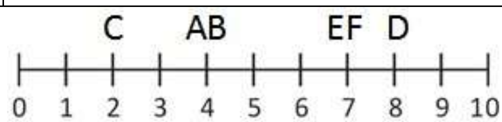
</table>

<u>EVALUATION REFERENCE (given by 6 initial samples)</u>

FABRIC HAND EVALUATION

	Fabric tactile properties		Fabric tactile properties
1	**Stiff : Rigide –Pliable : Souple**	**12**	**Non-full : Non-riche -- Full: Riche**
			
2	**Dead: Mort/intangible – Lively : vif**	**13**	**Rough: Rugueux (surface entière) – Smooth : Lisse (surface entière)**
			
3	**Non-draped: Non tombant – Draped : Tombant**	**14**	**Grainy: Granuleux -- Non grainy : Non granuleux**
			
4	**Crumply: Froissable--Wrinkle-resistant: Infroissable**	**15**	**With ridges: Stries -- Without ridges : Sans stries**
			
5	**Non-stretchy : Non élastique -- Stretchy: Elasitique**	**16**	**Bumpy: Accidenté -- Non bumpy : Non accidenté**
			
6	**Loose: Lâche -- Tight: Serré**	**17**	**Prickly: Epineux -- Non prickly : Non épineux**
			
7	**Flimsy: Fragile/peu solide -- Firm: Ferme**	**18**	**Fuzzy(downy):Duveteux --Non fuzzy :Non duveteux**
			
8	**Thin: Mince -- Thick: Epais**	**19**	**Non-sllippery : Non-glissant -- Slippery: Glissant**

			
9	**Light: Léger -- Heavy: Lourd**	**20**	**Harsh: Rêche -- Soft (surface): Doux (surface)**
			
10	**Hard : dur -- Soft(compression): Doux**	**21**	**Warm: Chaud -- Cool: Frais**
			
11	**Non-springy (in compression) Non élastique – Springy: Elastique (en compression)**		
			

- **Experiment II (b)** (Visual feature evaluation on 18 samples (6+12))

QUESTIONNAIRE:

VIISUAL FEATURE EVALUATION

NOM:		SEX:	F□ H□	AGE:	

SCALE: Échelle					
De 0 à 10 :					
Extremely	Very	Quite	Fairly	More than medium	Medium
Extrêmement	Très	Vraiment	Assez	Plus que moyennement	Moyennement
0	**1**	**2**	**3**	**4**	**5**
More than medium	Fairly	Quite	Very	Extremely	
Plus que moyennement	Assez	Vraiment	Très	Extrême-ment	
6	**7**	**8**	**9**	**10**	

EVALUATION

NOTICE: Every listed attribute should be evaluated. Please give an appropriate score according to every descriptor in the blank corresponding to each specific skirt.
N.B : Chaque attribut listé doit être évalué. Veuillez choisir une note, symbolisée sur l'échelle, qui vous semble la plus appropriée en fonction de l'attribut évalué et ce pour chaque numéro d'échantillon

Ⅰ. Details: Détails

A. Waist line: Ceinture

1. Outline of pleats

Clear	0	1	2	3	4	5	6	7	8	9	10	Fuzzy

①	②	③	④	⑤	⑥
⑦	⑧	⑨	⑩	⑪	⑫

2. Outline of pleats

Rigid	0	1	2	3	4	5	6	7	8	9	10	Soft

①	②	③	④	⑤	⑥
⑦	⑧	⑨	⑩	⑪	⑫

B. Area of abdomen and huckle
Partie ventrale et arrière (y compris la hanche)

1. Fitness to the body shape: Accord avec la forme du corps

Unfit: Incorrect	0	1	2	3	4	5	6	7	8	9	10	Fit: Correct

①	②	③	④	⑤	⑥
⑦	⑧	⑨	⑩	⑪	⑫

2. Pleats: Plis

a. Size: Dimension des plis

Small: Petite	0	1	2	3	4	5	6	7	8	9	10	Big: Grande

①	②	③	④	⑤	⑥
⑦	⑧	⑨	⑩	⑪	⑫

b. Distribution: Distribution des plis

Uneven: Non-Uniforme	0	1	2	3	4	5	6	7	8	9	10	Even: Uniforme

①	②	③	④	⑤	⑥
⑦	⑧	⑨	⑩	⑪	⑫

c. Effect of the pleats : Effet des plis

Non natural (with distortion): Non Naturel(avec déformation)	0	1	2	3	4	5	6	7	8	9	10	Natural (without distortion): Naturel (sans déformation)

①	②	③	④	⑤	⑥
⑦	⑧	⑨	⑩	⑪	⑫

C. Lower part of the skirt: Partie infèrieure

1. The extent to which the skirt expands from below the hip.
La capacité avec laquelle la jupe s'élargit en dessous de la hanche.

Not at all: Faible capacité	0	1	2	3	4	5	6	7	8	9	10	Extremely: Forte capacité

①	②	③	④	⑤	⑥
⑦	⑧	⑨	⑩	⑪	⑫

2. Waves: Vagues

a. Size: Dimension des vagues

Small: Petite	0	1	2	3	4	5	6	7	8	9	10	Big: Forte

①	②	③	④	⑤	⑥
⑦	⑧	⑨	⑩	⑪	⑫

b. Smoothness : Douceur

Not smooth: non lisse	0	1	2	3	4	5	6	7	8	9	10	Smooth: Lisse

①	②	③	④	⑤	⑥
⑦	⑧	⑨	⑩	⑪	⑫

c. Distribution: Distribution des vagues

Uneven: Non-uniforme	0	1	2	3	4	5	6	7	8	9	10	Even: Uniforme

①	②	③	④	⑤	⑥
⑦	⑧	⑨	⑩	⑪	⑫

3. Hemline: Ourlet

a. Consistency of wave heights (the vertical distance between each adjacent peak and valley)
Reproduction des hauteurs des vagues (distance verticale entre chaque pic et la vallée adjacente)

Inconsistent : Inégale	0	1	2	3	4	5	6	7	8	9	10	Consistent: Egale
①	②	③	④	⑤	⑥							
⑦	⑧	⑨	⑩	⑪	⑫							
b. Evenness of bottom edge (Whether the hemline falls on the same plane) Uniformité du tomber de l'ourlet (Si l'ourlet se projette sur un même plan)												
Uneven : Irrégulier	0	1	2	3	4	5	6	7	8	9	10	Even : Régulier
①	②	③	④	⑤	⑥							
⑦	⑧	⑨	⑩	⑪	⑫							
c. The extent to which the bottom edge curls outward. La capacité avec laquelle le bord du bas se retrousse vers l'extérieur.												
Not at all : Faible capacité	0	1	2	3	4	5	6	7	8	9	10	Very: Forte capacité
①	②	③	④	⑤	⑥							
⑦	⑧	⑨	⑩	⑪	⑫							
D. Color texture : Couleur												
1. Brightness of color: Éclat de couleur												
Dark: Sombre	0	1	2	3	4	5	6	7	8	9	10	Light : Claire
①	②	③	④	⑤	⑥							
⑦	⑧	⑨	⑩	⑪	⑫							
2. Vividness (A vivid color has higher saturation, thus is purer) Vividité (Une couleur vive a la saturation plus élevée, donc est plus pure)												
Muddy : Terne	0	1	2	3	4	5	6	7	8	9	10	Vivid: Vive
①	②	③	④	⑤	⑥							
⑦	⑧	⑨	⑩	⑪	⑫							
3. Cool-Warm: Froide - Chaude												
Cool : Froide	0	1	2	3	4	5	6	7	8	9	10	Warm :Chaude
①	②	③	④	⑤	⑥							
⑦	⑧	⑨	⑩	⑪	⑫							
E. Fabric sheen (light reflected from the surface of the skirt) **Lustre du tissu (La lumière réfléchie par la surface de la jupe)**												
1. Light intensity: Intensité de la lumière												
Weak (dim) : Réflexion faible	0	1	2	3	4	5	6	7	8	9	10	Strong: Réflexion forte
①	②	③	④	⑤	⑥							
⑦	⑧	⑨	⑩	⑪	⑫							

<table>
<tr><th colspan="13">Ⅱ. Shape : Forme</th></tr>
<tr><td colspan="13">1. Fitness: évaluation de l'adéquation entre la taille du vêtement et le morphotype du modèle qui le porte</td></tr>
<tr><td>Unfit: Mauvaise taille</td><td>0</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>6</td><td>7</td><td>8</td><td>9</td><td>10</td><td>Fit: Bonne taille</td></tr>
<tr><td>①</td><td colspan="2">②</td><td colspan="3">③</td><td colspan="3">④</td><td colspan="2">⑤</td><td colspan="2">⑥</td></tr>
<tr><td>⑦</td><td colspan="2">⑧</td><td colspan="3">⑨</td><td colspan="3">⑩</td><td colspan="2">⑪</td><td colspan="2">⑫</td></tr>
<tr><td colspan="13">2. Shapability: La forme du vêtement
Definition: The capacity to maintain the basic shape and structure of the specific type of skirt.
Définition: La Capacité de conserver la forme et la structure fondamentale de la jupe.</td></tr>
<tr><td>Incorrect: Incorrecte</td><td>0</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>6</td><td>7</td><td>8</td><td>9</td><td>10</td><td>Correct: Correcte</td></tr>
<tr><td>①</td><td colspan="2">②</td><td colspan="3">③</td><td colspan="3">④</td><td colspan="2">⑤</td><td colspan="2">⑥</td></tr>
<tr><td>⑦</td><td colspan="2">⑧</td><td colspan="3">⑨</td><td colspan="3">⑩</td><td colspan="2">⑪</td><td colspan="2">⑫</td></tr>
<tr><td colspan="13">3. Drapability: Drapé du vêtement
Definition: The capacity of a skirt to drape and shape in a natural and regular manner.
Définition: La capacité d'une jupe de draper et se former d'une manière naturelle et régulière.</td></tr>
<tr><td>Bad drapeability : Mauvais drapé</td><td>0</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>6</td><td>7</td><td>8</td><td>9</td><td>10</td><td>Good drapeability : Bon drapé</td></tr>
<tr><td>①</td><td colspan="2">②</td><td colspan="3">③</td><td colspan="3">④</td><td colspan="2">⑤</td><td colspan="2">⑥</td></tr>
<tr><td>⑦</td><td colspan="2">⑧</td><td colspan="3">⑨</td><td colspan="3">⑩</td><td colspan="2">⑪</td><td colspan="2">⑫</td></tr>
<tr><td colspan="13">4. Impression of the appearance: L'impression de l'apparence de la jupe</td></tr>
<tr><td>Rigid: rigide</td><td>0</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>6</td><td>7</td><td>8</td><td>9</td><td>10</td><td>Soft: douce</td></tr>
<tr><td>①</td><td colspan="2">②</td><td colspan="3">③</td><td colspan="3">④</td><td colspan="2">⑤</td><td colspan="2">⑥</td></tr>
<tr><td>⑦</td><td colspan="2">⑧</td><td colspan="3">⑨</td><td colspan="3">⑩</td><td colspan="2">⑪</td><td colspan="2">⑫</td></tr>
</table>

<table>
<tr><th colspan="13">Ⅲ. Dynamic Effect: Effet dynamique</th></tr>
<tr><td colspan="13">1. Balance: Equilibre
Definition: If a skirt has a balanced effect, the space constituted between each part of the skirt and the body is similar or complementary to its opposite part in volume and shape, and during the body movements, the skirt maintains a relatively static shape or rotates about the body at a somewhat constant speed.
Définition : Si une jupe présente un effet équilibré, l'espace constitué entre chaque partie de la jupe et le corps (aisance) est constant. Pendant les mouvements du corps, la jupe maintient une forme relativement statique ou pivote autour de l'axe du corps à une vitesse assez constante.</td></tr>
<tr><td>Not balanced: Non équilibré</td><td>0</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>6</td><td>7</td><td>8</td><td>9</td><td>10</td><td>Balanced: Equilibré</td></tr>
<tr><td>①</td><td colspan="2">②</td><td colspan="3">③</td><td colspan="3">④</td><td colspan="2">⑤</td><td colspan="2">⑥</td></tr>
<tr><td>⑦</td><td colspan="2">⑧</td><td colspan="3">⑨</td><td colspan="3">⑩</td><td colspan="2">⑪</td><td colspan="2">⑫</td></tr>
<tr><td colspan="13">2. Following property: Propriété de suivi
Definition: The degree to which the skirt swings immediately and easily to and fro following the wearer's</td></tr>
</table>

body movements.
Définition : Mesure avec laquelle la jupe suit immédiatement et facilement d'avant en arrière les mouvements du corps.

Not following : Mauvais suivi	0	1	2	3	4	5	6	7	8	9	10	Following : Bon suivi

①	②	③	④	⑤	⑥
⑦	⑧	⑨	⑩	⑪	⑫

3. Clinging effect: Effet d'ajustement
Definition: The effect of a skirt to cling to the body as the wearer moves.
Définition : La propension d'une jupe à coller au corps lors des mouvements du modèle.

Not clinging : Non collant	0	1	2	3	4	5	6	7	8	9	10	Clinging : Collant

①	②	③	④	⑤	⑥
⑦	⑧	⑨	⑩	⑪	⑫

4. Ethereality: Etre éthéré
Definition: A skirt that is ethereal is somewhat light and thin, so that it swings freely, loosely and elegantly as the wearer walks.
Définition: Une jupe est dite éthérée lorsqu'elle est plutôt légère et mince et qu'elle se balance librement et élégamment alors que le modèle défile.

Not etherealL : Non éthérée	0	1	2	3	4	5	6	7	8	9	10	Ethereal : Ethérée

①	②	③	④	⑤	⑥
⑦	⑧	⑨	⑩	⑪	⑫

4. Wave Flowability: La propriété des mouvements des vagues.
Definition: The degree to which the skirt waves flow fluently like the water during the body movement.
Définition: La mesure dans laquelle les vagues de la jupe coulent facilement comme l'eau lors des mouvements du corps.

Bad(Not-fluent): Non coulante	0	1	2	3	4	5	6	7	8	9	10	Good（fluent）: Coulante

①	②	③	④	⑤	⑥
⑦	⑧	⑨	⑩	⑪	⑫

6. Swinging range: Intervalle des mouvements de balancier
Definition: A big motion means the skirt has an obvious and big spatial movement as the wearer walks.
Définition: L'amplitude des mouvements est grande, cela signifie que la jupe définit de grands mouvements spatiaux alors que le modèle défile.

Small : Petite	0	1	2	3	4	5	6	7	8	9	10	Big : grande

①	②	③	④	⑤	⑥
⑦	⑧	⑨	⑩	⑪	⑫

7. Rhythm: Le sens du rythme
Definition: It is like the phenomenon, which usually appears in musical pieces and poems, of a harmonious sequence of the strongs alternating with the weaks and of the longs alternating with the shorts. <u>And in the current case, if a skirt has a good sense of rhythm, it swings to and fro according to the body movements in an even, regular, fluent and harmonious way.</u>

Définition : Identique au phénomène qui apparaît généralement dans des morceaux musicaux et des poèmes, d'une séquence harmonieuse où les moments (rythmes) 《forts》alternent avec des rythmes 《faibles》 et les 《lents》. Un vêtement a un bon sens du rythme, s'il balance d'avant en arrière de façon égale, régulière, harmonieuse lors des mouvements du corps.												
Weak in rhythm Faible en rythme	0	1	2	3	4	5	6	7	8	9	10	Stong in rhythm: Forte en rythme

①	②	③	④	⑤	⑥
⑦	⑧	⑨	⑩	⑪	⑫

ILLUSTRATION TO SKIRT PARTS (For visual feature evaluations):

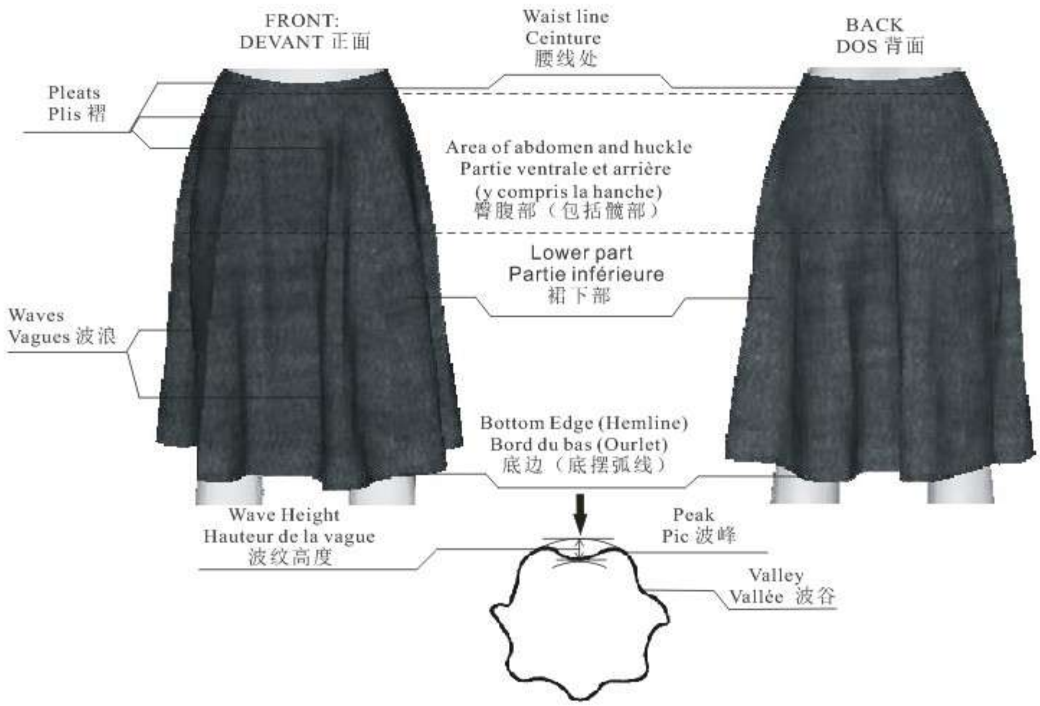


ILLUSTRATION TO COLOR BRIGHTNESS AND VIVIDNESS (For visual feature evaluations