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Intelligent Texture-Based Pattern Search, Classification and Interpolation for Woven Fabric Design

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Ph.D

The Hong Kong Polytechnic University

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Intelligent Texture-Based Pattern Search, Classification and Interpolation for Woven Fabric Design

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A thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy

February 2012

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Abstract

Abstract of dissertation entitled: Intelligent Texture-Based Pattern Search, Classification and Interpolation for Woven Fabric Design, submitted by Dejun Zheng for the degree of Doctor of Philosophy in the Department of Computing at The Hong Kong Polytechnic University in February 2012.

In the cognitive process of design activity, fabric designers conceive the color and texture composition not individually, but as an ensemble of tones, shades and tints that are created in the texture patterns of yarn and fiber materials. Perceptual features of natural textures as well as fabric textures have been extensively studied in the existing literature. However, no thorough investigation of the cognitive texture features of woven patterns in fabric design has been conducted so far. The present research uses cognitive informatics models to study fabric texture features in the process of woven fabric design. It provides a comprehensive framework to facilitate selecting and designing the fabric textures in the design process.

The research framework comprises cognitive fabric feature analysis and fabric texture operations in fabric pattern design, namely, fabric search, pattern classification, and woven texture interpolation with color theme-based texture synthesis. A novel object-attribute-relation (OAR) model is used to study fabric texture digitization and texture feature analysis. A relation between the high-level cognitive features and low-level perceptual features of fabric patterns in design activity is described. The cognitive features in fabric design are used to develop fabric texture operations. Examples of how cognitive features can be used to

perform texture selecting and synthesizing tasks are given.

There are three major contributions of this study to existing fabric texture analysis and research. (1) The study reduces the gap between the cognitive features of fabric textures in the design activity and the perceptual features of the textures in material operations. (2) New approaches for fabric pattern design are developed based on the cognitive color theme and interpolated woven patterns. (3) The research findings illustrate that fabric texture digitization methods and cognitive feature extraction in design activity are major factors in developing effective fabric texture operations.

List of publications

[1] D. Zheng, G. Baciu, and J. Hu, “Accurate indexing and classification for fabric weave patterns using entropy-based approach”, *in proceedings of 8th IEEE International Conference on Cognitive Informatics (IEEE ICCI’09)*, 2009, pp. 357-364.

[2] D. Zheng, G. Baciu, and J. Hu: “Entropy-based fabric weave pattern indexing and classification”, *The International Journal of Cognitive Informatics and Natural Intelligence*, vol. 4, pp. 76-92, 2010.

[3] D. Zheng, G. Baciu, J. Hu, and H. Xu, “Cognitive weave pattern prioritization: an application-oriented approach”, *in proceedings of 10th IEEE International Conference on Cognitive Informatics & Cognitive Computing (IEEE ICCI*CC’11)*, 2011, pp. 85-95.

[4] J. Zhang, G. Baciu, D. Zheng, C. Liang, G. Li, and J. Hu, “IDSS: a novel representation for woven fabrics”, *IEEE Transactions on Visualization and Computer Graphics*, 2012 (Accepted).

[5] D. Zheng, G. Baciu, J. Hu, and H. Xu, “Cognitive weave pattern prioritization in fabric design: an application-oriented approach”, *The International Journal of Cognitive Informatics and Natural Intelligence*, 2012 (Accepted).

[6] D. Zheng, Y. Han, G. Baciu, and J. Hu, “Design through cognitive color theme: a new approach for fabric design”, *in proceedings of 12th IEEE International Conference on Cognitive Informatics & Cognitive Computing (IEEE ICCI*CC’12)*, 2012 (Accepted).

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[8] G Baciu, D Zheng and J Hu, Digital technology and modeling for fabric structures, *Computer Technology for Textiles and Apparel*. Cambridge: Woodhead Publishing, 2011.

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Table of contents

List of figures

List of tables

Chapter 1:

Introduction

1.1 Research motivation

Fabric designers often look for inspiration from image collections according to the content-based features of the images. Among different image features, perceptual texture features are considered to be the most suited features for image texture information retrieval [1, 2]. These perceptual features are wildly used in machine vision systems, for example content-based image retrieval, classification and texture synthesis, where a designer may want to find images that contain a particular texture and use the textures of interest to create new textures. Despite the advances in the feature selection techniques and matching techniques, the current machine vision systems still have a major difficulty that it has yet to overcome, i.e., how does the observer relate the low-level features of the images to the high-level semantics of image contents [3, 4]?

Recently, research focus has been shifted from designing sophisticated low-level feature extraction algorithms to reducing the ‘semantic gap’ between the perceptual image features and the richness of human semantics. This present investigation focuses on fabric texture representation and texture operations in the context of fabric texture design. Fabric texture analysis and synthesis are achieved through the relationships between the perceptual texture features and cognitive features in the cognitive process of fabric design activity. This thesis covers the most recent investigations into texture-based approaches for fabric texture analysis. Furthermore, new higher level cognitive models are proposed for fabric design and classification.

1.2 Problem statement

In the textiles and clothing industry, fashion designers mainly use fabric texture collections to create new fabric designs according to fashion changes from year to year. A fabric swatch library and CAD (computer aided design) tools are indispensable to fabric designers in order to search the desired texture elements from the library and synthesize new fabric textures in a more efficient way. However, the current systems do not provide functions that can efficiently search fabric patterns and synthesize new fabric textures.

The current fabric search methods are based on numerical and alphabetical indexing, which provide simple text-based search and classification by production attributes of fabrics, such as sample item number, creation date, category name, material composition, and fabric density. In fact, these attributes contain little content-based information for designing fabric textures. Therefore, there is a lack of support from the search methods to the fabric texture synthesis and classification in fabric texture design.

On the other hand, both text-based annotations of the fabrics and the synthesis of fabric textures by the current commercial software, such as Photoshop and EAT fabric CAD are very tedious and error prone. A fabric designer may have to browse many fabric images by the heuristic annotations to find the desired texture elements. On the other hand, the designer needs to choose delicate operations of texture editing to create a compatible combination of textures and colors through a large number of trials. For these reasons, a desired fabric database management system for fabric design should facilitate both fabric search and texture operations.

1.3 Objectives

The main objective of the present research is to develop a complete programme of fabric texture management and design in the fabric database system. This objective encompasses three sub-goals (1) cognitive informatics models for reducing the gap between cognitive process of design activity and perception-based texture analysis during texture operations; (2) fabric pattern search and classification through cognitive texture features for fabric texture selection; and (3) fabric texture synthesis based on cognitive color theme and weave pattern interpolation. In this section, each sub-goal will be briefly described. Further details will be presented in following chapters.

- **Cognitive models of fabric texture representation**

Gabrieli noted that in computer vision, software engineering, informatics, and artificial intelligence, almost all hard problems that are yet to be solved, share a common root in the understanding of the mechanisms of the natural intelligence and the cognitive processes of the brain [5]. This leads to an emerging discipline of research known as cognitive informatics [6]. Cognitive informatics models are developed for extending human of intelligence, memory, and capacity of information processing. In this research work, cognitive informatics models are used to investigate the main components in the cognitive process of fabric design. These components are fabric image data, structured patterns and finally design theme of patterns.

Cognitive models for fabric texture design are built based on the process of the information transmission during fabric data collection, digitization, structure pattern extraction, texture analysis and operations. The cognitive models provide guidance (1) how to collect and digitize the fabric texture for the purpose of gathering and sorting fabric textures, (2) how to build the relationships between high-level cognitive features and low-level perceptual features, and (3) how to use digital fabric textures and cognitive design knowledge to synthesize and generate new fabric designs.

- **Fabric pattern search and classification**

Since fabric is interwoven with warp and weft yarns, the color and pattern effect of woven fabrics can only be generated through its own interlacing structure. Fabric designers choose the suitable interlacing structure for creating textures through the weave pattern maps that are interlacing probabilities of material units, such as fibers, yarns, and twisted yarn sets. To investigate the principal properties of woven structure, structural parameters extraction and analysis were proposed in [7]. The fabric defects detection and objective texture classification were reviewed in [8]. However, there is little research that focuses on weave pattern structure search and classification in terms of fabric pattern design.

Texture identification of material units is essential for fabric texture search and classification in fabric design. The influences of fabric image resolution on appearance can be investigated by experimental observations and cognitive interpretation of texture design. In the current investigation, fabric texture fingerprints and their attributes are used for search and classification of fabric patterns by design rules. The concept of fabric texture fingerprints described in this work is inspired by fingerprint recognition as one of the most widely used biometric identification technologies in the past half of a century with numerous applications to object recognition, indexing, classification, search, etc. Fingerprint identification, also referred to as individualization, involves an expert, or an expert computer system operating under threshold scoring rules, determining whether two friction ridge impressions are likely to have originated from the same finger or palm (or toe or sole).

The fabric fingerprints define major features to differentiate the design rules of fabric woven patterns. Fabric search and classification are based on these major features for the purpose of selecting and sorting fabric designs. There are three aspects in developing a fabric search and classification system:

(1) The fabric texture image acquisition and representation of material units at fiber-level and yarn-level,

(2) The texture-based detection of fabric design rules by using automatic and interactive methods,

(3) Fabric weave pattern search and classification based on texture design rules and cognitive texture features in the process of fabric texture design.

- **Fabric texture design and weave pattern interpolation**

Cognitive texture features of fabric design are used to prioritize texture elements and generate fabric weave patterns. Perceptual texture features deal with separate issues of texture properties and thus are not optimally suitable for the designer’s current interests. In [9], methods for extracting low-level perceptual texture features were investigated and classified into three categories: filtering, statistical and model-based approaches. In [10], the texture operation focused on texture replacement with low-level texture features. In these previous research studies, texture resolution, material digitization, feature extraction and texture operations were treated as different topics. Moreover, the effectiveness and the efficiency of the operations depend on a number of external factors, such as frequent changes in the material conditions as well as object data content or status. Thus, texture synthesis may introduce inconsistencies in the texture operations in the database management system.

In this work, an object-oriented database system is used. This makes use of the interactions of individual texture operations at each synthesis stage, so as to help user to find the principal texture features to be extracted, analyzed and manipulated. The resulting system will be a fully integrated knowledge base for fabric texture documentation and reusing. The consistency of the cognitive design theme for such a system is the major prerequisite for fabric texture operations. The objectives include: 1) development of an information flow framework to bridge fabric weave pattern selection and figured-pattern design activity in fabric database management system, and 2) demonstration and discussion of application-oriented texture analysis and operations experiments. This innovative research method not only ensures the connection of fabric texture analysis and synthesis from academic perspectives, but also provides a sound technical and management experience for fabric texture documentation and design in the textiles and clothing industry.

1.4 Contributions

Searching and sorting fabric weave patterns in a database can be a tedious experience in fabric design. Unfortunately, commercial software, such as Photoshop, EAT Jacquard design and Penelope CAD for woven fabrics, do not explicitly support these tasks. A fabric designer may have to search for suitable fabric images and carefully edit them to obtain a weave pattern map for simulation on the computer screen or production on the weaving machines. Furthermore, a large number of trials are often indispensible to achieve desired relationships between color and texture. Hence, a desired approach should automate searching and editing fabric colors and textures for fabric texture design. In this research, one of the major contributions lies in casting the process of cognition in fabric design as an integrated problem that deals with both color and texture synthesis combined with the selection and prioritization of texture elements. A new framework for fabric design is proposed that simultaneously considers the design of fabric color and texture effects in a fabric pattern.

Another contribution of this work is that the cognitive object-attribute-relation (OAR) model is proposed to reduce the gap between cognitive texture features and perceptual texture features in fabric design operations. In the OAR model, novel techniques of fabric image acquisition and perceptual texture feature extraction are developed. Experimental findings illustrate that multi-resolution and multi-direction image features are very helpful to improve the accuracy of texture extraction algorithms. Automatic and interactive weave pattern extraction methods are discussed through experimental validation. Cognitive texture features are calculated according to the weave pattern structures and cognitive relationships of perceptual features and cognitive features in the fabric production process. Therefore, fabric texture search and classification are conducted based on these cognitive features in fabric data management and design.

On the other hand, fabric texture design methods are formulated as an optimization problem that quantifies texture and color to maintain the consistency of data, patterns and knowledge in the information transmission flow. The underlying cognitive relationships that connect textures and color tones from different image sources are explored to maintain the same theme in the cognition of observers or in the current case, fabric designers. The system can automatically interpolate Jacquard fabric patterns through modifying and changing the composition of weave patterns and colors of images. Fashion designers can use the system to transfer both color and texture from an image to the desired fabric simulations. The system can synthesize fabric textures from texture and color databases and present the textures in application boards that rival complex commercial designs even by professional designers.

1.5 Organization

The remainder of this dissertation is organized as follows. Chapter 2 reviews different methods and models mainly for content-based fabric perceptual feature extraction. The advantages and disadvantages offered by the various algorithms are discussed. Chapter 3 develops cognitive models and texture-based fabric structure representation for fabric cognitive feature analysis. Fabric texture operations including search, classification and pattern interpolation, are detailed in Chapter 4, Chapter 5, and Chapter 6, respectively. A systematic flow of fabric texture operations in color and texture databases and the examples of design applications are also given in Chapter 6. As a summary of this research work, conclusions and future directions are discussed in Chapter 7.

Chapter 2:

Literature Review

2.1 Overview

The interdisciplinary field of texture analysis and design operations includes diversified subsequent areas of theoretical and experimental knowledge of constructional, technological, system, hardware, and software. The dynamic development of these techniques implies that their applications are broadened in many fields of science. The feature extraction and displaying of fabric texture properties are among the two of classical problems in texture analysis and design. Both of them continue to arouse further research interests because of limited success so far in the past decades. In this chapter, the existing literature related to fabric feature extraction, texture analysis and operation, is reviewed.

2.2 Methodologies for fabric texture-based analysis

There are several surveys for general texture analysis. In [11], the basic issues of texture analysis, such as translation, rotation, affine, and perspective transform have been discussed. A survey is dedicated to texture segmentation and feature extraction particularly for various unsupervised applications [12]. Specific applications of computer vision-based feature extraction surveys had also been addressed in [13] and [8]. Tuceryan and Jain [14] identified five major categories of features for texture analysis: statistical, geometrical, structural [15], model-based and signal processing features.

Various imaging techniques and image processing methods were proposed for fabric feature extraction and analysis. CT scanning technique has been used to trace fabric yarns and reconstruct the three-dimensional geometry structure of a fabric [16, 17]. The majority of research focuses on fabric feature extraction and feature analysis by image processing methods.

2.2.1 Statistical methods

Statistical methods are widely used to summarize or describe data pertaining to the collection of textures for feature analysis, interpretation and presentation. The statistical approaches form the majority of work reported for fabric texture analysis, including fractal dimension, first-order statistics, cross correlation, edge detection, morphological operations, co-occurrence matrix, eigenfilters, rank-order functions, and local linear transforms. Table 1 lists major research related to fabric feature extraction and texture analysis by statistical approaches.

Table 1. Statistical approaches for fabric texture analysis

Approaches	References
Autocorrelation function	Kang and Kim (1999), Jeon et al. (2003), Wu et al. (2005), Robert and Mieczyslaw (2006), Zhang and Bresee (1995)
Morphological operation	Huang and Bresee (1993), Robert and Mieczyslaw (2006), Kuo et al. (2004), Ajallouian et al. (2009)
Artificial neural network	Jeon et al (2003), Lee (2004), Kuo and Tsai (2006), Kuo and Kao (2007)
Co-occurrence matrix	Bodnarova et al. (1997, 2000), Latif-Amet et al. (2000), Siew et al. (1998), Tsai et al. (1995), Lin

	(2002), Kuo and Tsai (2006), Salem and Nasri (2009b), She et al. (2005)
Edge detection	Lee (2004), Yu et al. (2009), Yu (2008)
Gray level statistics	Liu and Li (2008), Kuo and Su (2006), Kuo et al. (2007), Su et al. (2010)

Autocorrelation combines all the image fragments and it is often used to characterize repeated structures in the fabric image. This technique makes it easy to reproduce the repeated pixel units in relation to the whole image analyzed [18, 19]. In [20-22], autocorrelation function is used to determine structural repeat units of fabric weave pattern. In [20], the testing image and the original calculation results by autocorrelation function showed that the autocorrelation function has difficulty in accurate recognition of weave repeat unites due to irregular distributions along warp and weft directions caused by yarn skewness and displacement [23]. The projection profile for gradients was shown to obtain better extraction features of fluctuation than the one for grey-levels [22]. The experimental results presented in [22] were accurate for high brightness contrast of fabric images with regular yarn interlacing appearance; nevertheless, autocorrelation function is not applicable for fabric weave patterns with irregular colorway layout.

Erosion and dilatation are among the commonly applied morphological operations in the shape analysis of fabric textures. In [19, 21, 24], the authors used erosion and dilatation on the mask processed by the threshold procedure to analyze yarn interlacing regions. Morphological features were used to describe fabric texture features in [25, 26], such as porosity, fiber orientation distribution, and fiber regularity distribution. According to Zhang and Bresee [18], applying morphological methods in image analysis requires greater calculation power compared with using the statistical methods, considering the higher quality of processing the image mask demanded. Furthermore, morphological methods are limited to extract fabric texture features when long hairiness exists on the fabric surfaces.

Several studies have been performed on fabric texture classification by using neural network. In [21], the ratio values of crossing points were used as the input pattern of a neural work and the neural network was then trained by the LVQ (learning vector quantization) algorithm to classify fabric weave pattern. The edge information was incorporated into multi-layer neural network for classification of fabric textures [27]. LVQ was also adopted as a classifier to categorize the class of weaving texture [28]. Recently, another related work for fabric classification using SOM (Self-Organizing Map) appeared in [29]. However, a large number of fabric texture classes with large intra-class diversity remain major obstacles in neural network [30] and Genetic SOM [31]. The assumption used by neural classifiers in the analysis of fabrics is that the yarn spacing and intersection segments are easy to identify. In fact, most of fabric textures are not exactly regular and it is often difficult to locate and extract the intersection areas of yarns in a fabric image. Furthermore, there are still a number of unsolved problems in neural network feature extraction methods, including the lack of a profound theoretical basis, the problem of network architecture design, and the black-box problem as pointed out by [32].

The spatial grey level co-occurrence (SGLC) matrix is a widely used statistical tool for detecting fabric features [33-35]. SGLC has been used to evaluate the carpet wear in [36] and it was proved to be popular in surface evaluation for fabrics [37] and wood [38]. Lin [39] evaluated the efficiency and accuracy of a way to detect a fabric's weaving density using a co-occurrence-based method and the finding was that the calculation precision for the plain weave was far better than for twill and satin weaves. The features extracted using SGLC were evaluated by [28, 40, 41] and it was shown that SGLC has better ability of texture description in fabric classification than wavelet analysis, such as Gabor wavelet and wavelet decompositions [40, 41].

There are operational problems when the co-occurrence matrices based approaches are applied to extract fabric texture features. It is a computationally demanding process to determine the co-occurrence matrices and there are up to 14 features which are extracted from each co-occurrence matrix. There is a feature-selection problem in such detection approaches for different types of fabric texture and the feature determination therefore needs to be customized for different texture properties.

The amount of gray level transitions in the fabric image may represent lines, edges, point defects and other spatial discontinuities. The distribution of the amount of edge per unit area is an important feature in the textured images and were used to detect fabric texture defects [8, 42, 43]. Lee used edge detection approach to get second-order features for classification and the results showed that this method was better than texton-based extraction method [27]. A new model named active grid model (AGM) was proposed in [44] to identify weave pattern of fabrics. The proposed model was based on active contours or snakes algorithm introduced first in [45] which was energy-driven curves moving with images to auto-adaptively deform and describe the shape of yarns in the fabric images. Several experimental results presented by the authors indicated that the system was capable of classifying fabric weave patterns.

Grey relational analysis was also used to identify fabric texture [46, 47]. The grey relational analysis of fabric images was defined in [48, 49]. The grey relational approach was applied to analyze the correlation in the random factor sequence of feature indexes after some data processing and thus determine the texture type of the designated fabric on the basis of the highest correlative degree [46]. There were six types of fabric texture used for materials classification in the study, i.e. cotton, polyester, silk, rayon, knitting and linen. If there were existing shadows in the fabric images, the grey levels in the images would be distributed unevenly and that would lead to difficulty or even failure in classification.

2.2.2 Frequency and spatial domain methods

Since homogeneous textile fabrics consist of texture units arranged under a deterministic rule, the high degree of periodicity of basic texture units allows the usage of signal processing-based approaches for the extraction of structural parameters of fabric textures. Early work on assessment of carpet wear suggested that it might be possible to find spatial-frequency domain features less sensitive to noise and intensity variations than those features extracted from spatial domain [36]. Signal processing-based approaches have been one of the most widely used feature extraction approaches. Table 2 summarizes the major signal-based approaches adopted for structural parameter extraction in fabric texture analysis.

Fourier transform has been shown to be efficient for fabrics with high repetitiveness. When the yarn distortion and slippage are not sharp, the locations of yarns could be detected by Fourier transform method. Taking into account that a woven fabric is of a periodic texture, it seems quite natural to investigate how to extract the weave pattern information based on yarn location detection using Fourier transform [50-52].

Table 2. Signal processing-based approaches for feature analysis of fabrics

Approaches	References
Fourier transform	Xu (1996), Kinoshita et al. (1989), Wood (1990), Ghane et al. (2010), Millan and Escofet (1996), Yu et al. (2007), Pan et al. (2009b), Randen and Husoy (1999), Moussa et al. (2010), Kinoshita et al. (1989), Ravandi and Toriumi (1995), Escofet et al. (2001), Rallo' et al. (2003), Akiyama et al. (1986)
Gabor filter	Salem and Nasri (2009b), Arivazhagan et al. (2006), Beirão and Figueiredo (2004)
Wavelet transform	Daugman (1980), Peng (2007), She et al. (2005), Kuo and Tsai (2006), Kuo and Kao (2007), Su et al. (2008)
Finite impulse response filter	Kumar and Pang (2002), Kumar (2003)
Wiener filter	Liqing et al. (2008)

An image of periodic structures can be described as the convolution of an element unit by a two dimensional comb function which establish the periodic pattern [53]. The fabric structure thus is recognized and classified by the angular correlation of the sample spectrum and the reference spectrum in Fourier domain [54, 55]. In [56], the fabric image has been analyzed in HSL color space by Fourier transform. The power spectrum image derived from Fourier transform of fabric image was analyzed and filtered [9]. Peaks in the power spectrum image stand for frequency of yarn periodic elements from which basic weave patterns, such as plain, twill [57] and stain, could be discriminated by locations of power spectrum peaks [50, 58-60].

Ravandi and Toriumi used Fourier transform to evaluate fabric appearance characteristics such as directionality, protruding yarn density, and yarn spacing for plain weave fabrics [58]. Two-dimensional Fast Fourier transform was used to analyze both weft and warp yarns of fabric image. The 2-D pattern power spectra offers a special angle to view weave pattern types of plain, twill and satin. However, the method was not so robust and still qualitative and rather approximate [60]. Recently, minimal weave repeat definition and identification using spatial and Fourier domain was also proposed along this research direction [61, 62]. Since the optical behavior of lenses and diffraction gratings could be described by Fourier transform theory [63], Akiyama et al. [64] used diffraction of laser light by regular arrangement of yarns in a fabric to characterize weave pattern types. This method can be bracketed into Fourier transform method.

Several researchers have applied Gabor filters to fabric texture recognition and classification. Salem and Nasri had tested Gabor filter to recognition and classification of twill, satin and plain weave patterns [40]. According to the report, GLCM method with classification accuracy of 97.2% performed better than Gabor filter (best result was 96.9%). The fusion of Gabor filter and GLCM gave the best classification result (98%), but a single method of GLCM had better running time. Gabor filters are also used in fabric defects detection and classification [65, 66]. Gabor filters have been widely used in perceptual feature detection and extraction for different texture categories, such as wood, sand and grass. However, fabric texture may contain subtle perceptual texture difference while there is underlying essential difference in structure. For instance, plain and twill may be perceptually very similar but they are different structures in fabric design.

Wavelet transform is also used to differentiate fabric textures in both spatial and spatial-frequency domain [67, 68]. She et al. used a feature set extracted from two-level distinct wavelet of decomposed sub-bands and these features were then used to classify fabric weave pattern types. Experimental results of the recognition rate was 79% [41]. The two-layer wavelet analysis was applied to divide an image into sub-images by [28]. Low frequency sub-image was taken in the second layer of wavelet transform and the diagonal high frequency sub-image was used to calculate the co-occurrence matrix. The classification accuracy of fabric weave pattern was about 95% through LVQN (Learning Vector Quantization Networks). In [29], wavelet was also utilized to display texture characteristics of a fabric image. Su also proposed to use wavelet transform to acquire image features to recognize types of fabric texture [30] and the recognition rate amounted to 97.67%. Similar to Gabor filters, Wavelet transform are designed to differentiate major perceptual difference of fabric textures.

Other analysis techniques including finite impulse response (FIR) filters and Wiener filters were adopted for fabric texture feature extraction. Since fabric surface appearance is very complex due to irregular arrangements of yarns and fibers, fabric textures that produce very subtle light intensity transitions are difficult to identify. A potential solution to extract features from such textures was to employ optimal FIR filters. The related work was detailed in [69, 70]. In [71], a fabric image was decomposed into horizontal and vertical sub-images by using Wiener filter to warp and weft yarn location analysis. A Wiener filter is not an adaptive filter because the theory behind this filter assumes that the inputs are stationary. Therefore, the filter needs to be customized for different fabric textures. There were only three examples tested in the report.

2.2.3 Model-based methods

The model-based clustering methods were used to extract structural parameters from fabric images. Ajallouiana et al. used fuzzy c-means clustering techniques to determine the second threshold for generating the information of weave pattern in the form of black and white blocks [24]. Pan used a color-clustering scheme for yarn colorways detection [72-74]. The proposed scheme involved fuzzy C-clustering (FCM) and Hough transform [75] to locate the colorways of yarn profiles. As described in [73], the performance of this algorithm was excellent for all colored fabric images. The method is not suitable for analyzing fabric structural parameters when the image is dominated by grey color. Pan also tried a genetic algorithm-based method to detect the layout of color yarns [76].

In [26, 77], FCM was performed on multi-scale invariant texture features of gray level co-occurrence matrix to classify yarn crossed state of warp and weft. There was a geometrical method developed in [78]. The fabric weaving types were identified on the basis of geometric features of yarn distribution. There were 20 samples used for validation and the method was proven to be suitable for characterizing regular texture of fabrics, namely, fabrics have high clarity quality in terms of yarn configuration and crossing point profiles. Nishimatsu proposed an automatic recognition method also based on yarn float and crossover point shape analysis. Cross points of yarns are recognized by edge enhancement, threshold process, smoothing, mosaic averaging, and meshing [79].

2.3 Methodologies for fabric texture-based operations

Texture feature extraction and analysis are the key problems in texture operations, such as search, classification and interpolation or so called re-design. Texture operations give feedback to the former and refine the existing features or provoke new features of interest to be analyzed. There are numerous studies on general issues and algorithms of image search, classification, and texture synthesis. Recent years have seen a trend in computer science, showing that users are beginning to pay significant attention to texture-based image operations.

Image search or retrieval is one of the most important examples of image operations. The traditional content-based retrieval (CBIR) systems have many limitations. For a given query image, the CBIR system is to find the most similar images stored in the database. The search process relies on the use of image descriptors which are characterized by two functions [80, 81]: feature vector extraction and distance measurement function. Usually, different descriptors are statically combined and the combination is fixed. The descriptors are applied to process all queries submitted to the retrieval systems. Therefore, similarity of images is thus considered as a simple matching between low-level features and high-level concepts. Image content-based representation and understanding have not been studied well and still offer a challenge to researchers and scientists.

A wide variety of statistical methods have been proposed for texture classification. Most of the developed texture classification techniques are characterized by two properties, noise robustness and global and/or local texture descriptors [82, 83]. These techniques provide possible solutions to general appearance classification. However, few of these methods consider micro and macro texture structure properties. A single view of appearance may reveal a little underlying physical material meaning and thus cannot meet application needs in many situations. For example, these classification techniques provide little classification details of fabric texture characteristics, such as weave pattern, material properties, color layout, etc. Many users may have found complex parameter configuration daunting. Texture classification, therefore, is a comprehensive problem, which should be further studied in a systematic framework.

Texture interpolation refers to texture re-design or synthesis given the consideration that a new texture is created based on the existing patterns. In digital image processing and computer graphics communities, there is much work on texture design and synthesis. These studies are concerned with synthetic texture and its applications to scene synthesis, animation and special effects. In [10], a new texture was generated as a result of operations of the deformed fields in geometry, lighting and color. The authors used the multiplication techniques controlled by a weight factor in which the pixel-wise magnitude of a deformation field was manipulated. When the value of the weight factor is equal to 1 the deformation field is thought of faithful to the input; when the value is not equal to 1, i.e. the increment or decrement of the deformation value, the magnitude of the deformation field departure is considered as the new texture generation process. Brick wall texture and cloth texture were used as test examples.

In [84], a system for designing new textures induced by an input database is presented. By capturing the structure of the induced space through a simplicial complex, a user can generate new textures by interpolating within individual simplices. Cloth textures were used as examples. The experiment could not provide fabric details in the generated textures. Thus, a customized texture synthesis approach for fabric needs to be further investigated.

2.4 Summary

In this chapter, computer centric approaches for fabric feature extraction and texture classification have been reviewed. Many researchers have been dedicated to resolve the problem of fabric texture analysis by machine algorithms but have not found a solution for an intelligent analysis system. In the processes of fabric texture analysis, these approaches provide solutions to texture understanding, analysis and classification at the perceptual level.

Examples of failed texture feature extraction based on perceptual similarity metrics [2] imply that it is difficult to overcome the disadvantages and limitations of a perception-based feature extraction method in the fabric texture analysis and operation system. Furthermore, the perception-based approaches focus on objective feature extraction and typically provide little interactive functions for attracting improvement effort from the user. Therefore, both perceptual and cognitive understanding of texture features are indispensable in fabric texture analysis.

Chapter 3:

Cognitive Models for Fabric Texture Analysis and Operations

A texture is perceived in a set of interpretive cognitive processes of the brain at the subconscious function layers, which detects, relates, interprets, and searches internal information in the memory [6]. Memory is the foundation for maintaining a stable state of a conscious system and it plays an important role in object perception and recognition. Humans prioritize real entities according to virtual image in the memory and extract attributes to build a connection or an interrelationship between a pair of object-object, object-attribute, and/or attribute-attribute [6, 85].

Texture management systems, especially those that offer navigation of data processing functionality, have a particular challenge around cognitive interpretation of texture features. So the plan of seeking a systematic and effective way to continuously exploit cognitive texture features will be the key of development of an intelligent texture analysis and operations system. In recent years, the internal information processing mechanisms and processes of the brain, especially their engineering applications by using an interdisciplinary approach, have attracted a lot of research interests [86]. The interdisciplinary approach, including disciplines such as psychology, cognitive science, physiology, computing and neural science, is considered as a promising approach to model cognitive perception in natural intelligence.

In this study, an interdisciplinary approach that involves disciplines of cognitive computing [6, 85], material science, textile engineering, image processing and computer vision is used to investigate the cognitive features of fabric textures and their cognitive model in texture operations. First, an OAR model for fabric weave pattern is proposed to extract the essential features for indexing and grouping the weave patterns. Second, a cognitive informatics model for fabric texture operations is presented in which the key connections between the internal manipulation engine and external real fabric patterns are defined. Third, fabric texture fingerprints, i.e. the major features of woven pattern design rules are developed based on the cognitive models for fabric texture analysis and operations.

3.1 OAR model for fabric texture analysis

The cognitive model of the brain and memory function models are proposed and investigated in [5, 6]. Memory plays an important role in natural intelligence and is used to explain a wide range of fundamental phenomena in art, material science, mechanical engineering, psychology and cognitive science. In this section, a cognitive model for fabric texture analysis is developed based on object-attribute-relation (OAR) model of long-term memory (LTM) [6].

LTM is a permanent memory that human beings rely on for storing acquired information in terms of facts, knowledge and skills. During the design process, a designer selects weave patterns and creates new fabric designs. Both weave pattern selection and design activity are highly related to human LTM functions. The LTM-based texture interpretation for a fabric design in human brain is unlimited, because of the enormous number of neurons and many more potential synaptic connections in the brain. OAR model is a cognitive model of LTM, which explains how information or knowledge is represented in LTM and the model is described as a triple:

$$C \mathrel{\hat{=}} (O, A, R) \tag{1}$$

where C represents the cognitive OAR model for object analysis, O is a finite set of objects indentified by symbolic names, A is a finite set of attributes for characterizing an object, and R is a finite set of relations between an object and other objects. For fabric texture analysis, Cognitive Weave Pattern OAR model ($CWP-OAR$) is developed as follows:

$$CWP-OAR \mathrel{\hat{=}} (T, A, R) \tag{2}$$

where T is a finite set of weave patterns. R is a finite set of relations of the attributes of weave patterns. A is a set of attributes for characterizing fabric weave pattern properties, which is given by:

$$A = \{M, V, F\} \tag{3}$$

where M is the feature vector of material structure complexity which is related to information entropy [87] and texture regularity [10], V is the feature vector of structural appearance which is a grouping function of objects, and F is the feature vector of cognitive tracking features that detect repetitive patterns [88, 89]. These feature vectors are developed to describe the basic attributes of fabric weave patterns. These attributes of fabric textures are detailed as below:

First, fabric weave pattern complexity can be considered as the complexity of the material structure. The physical structure is formed during the weaving process of production in which the yarns are inter-woven together. Since a binary-valued weave pattern can be used to express the complete interlacing structure of a woven fabric without information loss, the distribution complexity of the points in the weave pattern thus corresponds to the material structure complexity of a fabric. In practice, fabric designers associate the weave pattern to the texture appearance of the final product. During the weave pattern selection process, designers compare and rank weave patterns according to the regularity or complexity of the distribution of warp and weft points. Hence, from the view of weave pattern selection in the design process, the weave pattern complexity is essential for indexing the material structure complexity.

Second, fabric appearance depends on its material units that are characterized by their structural appearances. The material units include fiber and yarn in a fabric. In the formation of a fabric structure, the appearance of the fabric is attributed to the spatial distribution of material units to be shown on the surface of the fabric. There are two aspects to describe the material units. The first one is the fingerprints of the material unit, fiber or yarn, which can uniquely define its characteristics of structural appearance at the micro level. The second one is the spatial distribution of material units on the fabric surface, which forms the texture objects on the fabric pattern. For example, a star pattern can be created by a group of warp floats on a plain background weave in which the shape of the yarn floats is a star pattern. Therefore, the clusters of yarn floats of warp and weft will mainly determine the surface structure appearance of a fabric. The clusters of yarn floats are considered to be the objects of interest distributed in a weave pattern, which are used as the global texture feature to group or categorize a weave pattern in this study.

Third, repetition size and content richness are considered as the basic features among different texture features of periodic patterns [90]. The cognitive features refer to the basic features that can be considered as major characteristics for texture pattern perception and understanding in fabric design activity. A feature-based texture analysis system is by and large a vision system and no feature-based vision system can work unless good features can be identified and tracked in the context of applications [91]. Traditional methods for fabric texture analysis and operations are based on physical point's pattern recognition [22, 34, 46, 60, 92]. In this study, the global texture feature of texel and its repetition information are used as the cognitive tracking features to describe the essential arrangement of fabric textures. Specifically, the cognitive tracking features are used to facilitate fabric texture operations, such as the search and classification of fabric images according to their repetition size and content richness.

3.2 Cognitive informatics model for fabric texture operations

Based on the cognitive model of brain developed in [6, 85], the cognitive informatics model for fabric texture operations is developed in Figure 1. The cognitive informatics model describes the information flow for fabric texture analysis and its operations. It can be considered to be a symmetric processing. The left part is the observations on patterns, and the right part expresses the knowledge about patterns. From top to bottom, there is a pattern for each layer: (1) texton at the first layer [93], which is the basic components of a fabric pattern that may include ideal color and texture effects in a fabric pattern; (2) texel at the second layer, which is one complete pattern of the periodic patterns of a fabric pattern; and (3) figured-pattern at the third layer, which is a meaningful pattern that is related to the high-level concept or description of objects in a fabric pattern, in terms of both color and texture effects, that is called a cognitive theme. These layers describe a hierarchical structure of pattern reception level from micro to macro level. In this study fabric texture is then defined as the patterns in the three layers.

For concreteness, the texton in a fabric expresses the yarn interlacing points that include warp and weft points on the fabric surface and their colors. Further, the description of texton is related to a weave pattern description at yarn level. Next, the texel can be considered to be a pattern, which is a rectangular unit of a fabric pattern. This assumption is reasonable for fabric production since a woven fabric only has weft (horizontal) and warp (vertical) yarns. Therefore, one complete pattern of the repetitive structure is a rectangular shape.

On the other hand, figured-pattern of a fabric is a combined pattern of fabric color and texture. Specifically, the combination process is related to the design process and its understanding process that connects texton, texel and finally figured-pattern. The combination process is implemented as weight functions of attributes of patterns. Note that the function of a figured-pattern is different from a texel pattern. For example, the former can express the regularity of the texels and the number of repetition times of texels in a fabric, which conveys meaningful information in applications.

In the cognitive informatics model of fabric texture operations, the external world can be implemented at the user interface part by inputting fabric texture patterns at different observation levels. The internal world refers to the internal feature extraction and relation association process, in which the fingerprints, attributes and relations are defined in the abstract layer for fabric texture analysis and operations. Specifically, fingerprints in the image layer refer to the abstract representation of attribute combinations. Attributes are the basic features that can describe the properties of textons and texels independently.

In the abstract layer, attributes are connected as a result of applications of texture operations. The applications in the process of texture operations are related to high-level concepts based on knowledge and skills that are subject to updating and maintenance. For instance, the relation association process in the central part may depend on the presentation way of textons, texels and figured-patterns. Once the relation association process is completed, new expressions of textons, texels and figured-patterns will be formed. In this way the unknown patterns and their Meta fingerprints or attributes then considered to be the known patterns and the derived fingerprints or attributes.

There are several important assumptions made in this model. First, the information transmission paths are not purely parallel; second, the cognitive relations are governed by a theme or a topic. Thus, the major difference between the traditional perception-based feature and the cognition-based feature for attribute representation is that: the former is a simple translation process in independent layers of textons, texels and figured-patterns, while the latter is not which is a more comprehensive description. Moreover, the proposed model explains the cognitive information flow for fabric pattern analysis and its operations in fabric pattern design process in which fabric designers use existing patterns at different levels and combine the essential attributes through the intermediate linkages to express knowledge and skills.

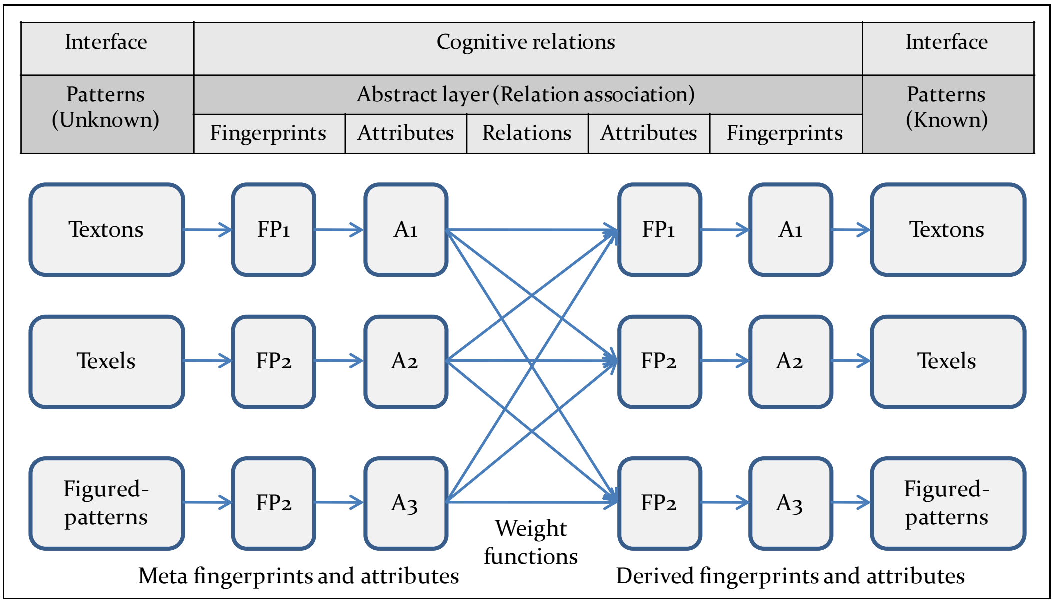


Figure 1. Cognitive informatics model for fabric texture operations.

The cognitive model is looped as thinking, reasoning, and other high-level cognitive processes [85]. Internal fingerprints are not only related to input patterns, but are also eventually connected to known textures. The link in loop in the internal texture operation engine makes it possible to transmit and update knowledge in abstract layer according to the application concepts and themes. It means that the information of input fabric textures includes not only the information in Visual Sensory Memory (VSM) but also other information stored in LTM.

Based on the OAR model and cognitive informatics model for texture operations, the abstract layer can be represented by a set of fabric textures, attributes, and relations, as described in $CWP-OAR$ model in Section 3.1. As discussed in Section 3.1, fabric weave pattern has three essential properties: material structure complexity, structural appearance, and repetition features (cognitive tracking features). At the texton layer in the cognitive informatics model, the pattern representation can be described by its fingerprints and the internal relations of basic features. Specifically, the presentation can be modeled by a relation reconfiguring scheme as shown in Figure 2.

Importantly, note that the basic feature extraction for texton layer may include the features from texel layer and even figured-pattern layer. The reason is that the attribute relations in the cognitive informatics model for fabric texture operations are interpreted as basic features in the implementation model. In addition, the central part of the implementation scheme indicates that the theme of is texton layer operations, such as search and classification, is the similarity measurement. To that end the indexing and grouping function definition is the key to fabric texture operations at the micro level.

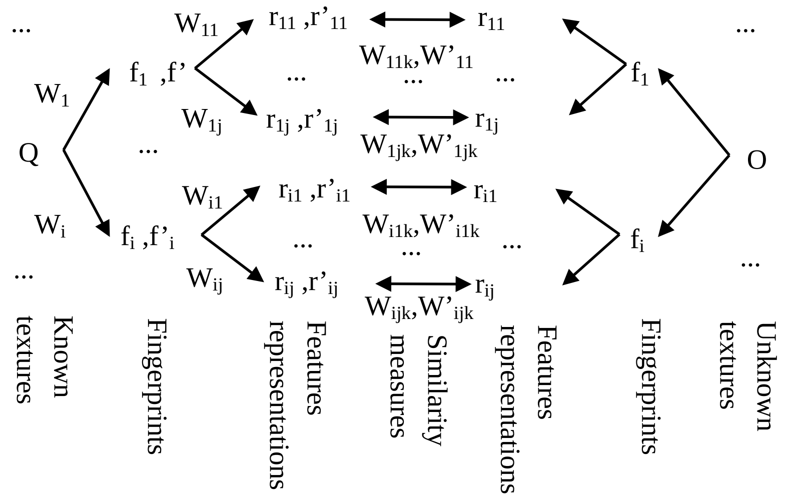


Figure 2. The implementation scheme of weave pattern search and classification based on the OAR model and the cognitive informatics model for fabric texture operations.

In the proposed scheme, O and Q are texture objects in $CWP-OAR$ model, i.e., unknown and known textures in the cognitive informatics model for texture operations. f can be considered to be the attributes in $CWP-OAR$ model and fingerprints in the cognitive informatics model for fabric texture operations. r is the set of relation representation in $CWP-OAR$, that is, the abstract layer relation set of attributes in the cognitive informatics model.

An algorithm for the evaluation of user relevance feedback was introduced in [94]. Based on the algorithm, the reconfiguring scheme of the relation set is comprised of four steps: i) show a small number of known textures specifying their application environments (texture application objects); ii) the user indicates an interest in fingerprint representations by assigning each weight value W for Q in Figure 2; iii) learn the user needs by relevance feedback of Q; and iv) apply each weight value W for Q to O.

3.3 Texture fingerprints

To systematically understand and identify fabric texture properties, the development of fabric texture fingerprints will be very useful in texture design operations, such as identification of texture properties, digitization, indexing, searching, classification and synthesis of textures. The OAR model for fabric texture analysis and cognitive informatics model for fabric texture operations will provide guidance to develop fabric texture fingerprints by the method of systematic analysis. The method of fabric texture fingerprint development includes three steps, as described below:

Step I, conducting a systematic review of fabric texture properties to identify significant factors in the process of fabric texture production.

Step II, implementation of OAR model for fabric texture analysis as detailed in Section 3.2.

Step III, defining fabric texture fingerprints by associating a set of basic features to the main properties of fabric material units at yarn level and fiber level.

Fabric texture fingerprints will be developed using the proposed three steps.

Each step is detailed in a subsection.

3.3.1 A systematic review of fabric texture properties

The fabric product used in daily lives, such as garment, curtains, and upholstery, is designed to achieve aesthetic or functional features. The modern technologies for fabric texture design and production are developed from the complex and lengthy socialization and maturation process of the human being. There are various fabric texture properties to be considered for fabric evaluation in both design and production process. To better understand the properties of fabrics, a systematic review of the fabric texture is needed.

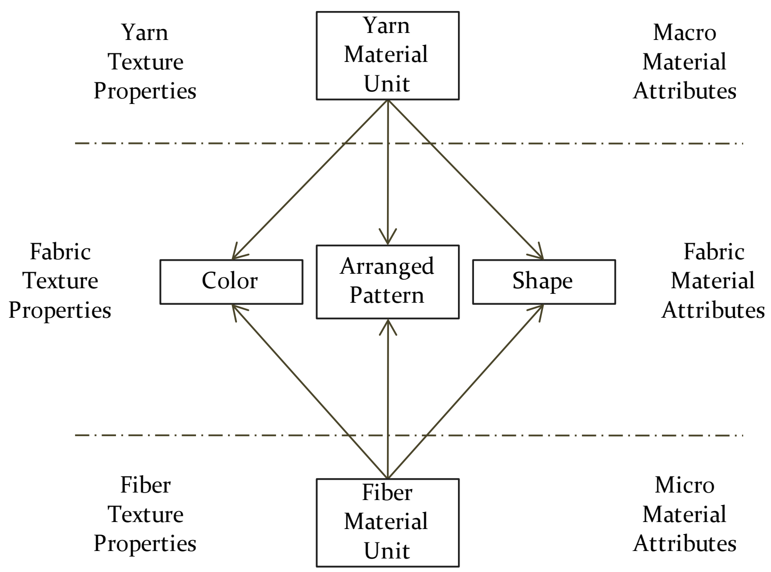


Figure 3. A layered relation between texture properties and material attributes.

When a fabric is constructed, the choice of material and finish is most important as it determines the final appearance and wearing qualities of the fabric. The most important properties of materials and finish are contained in the appearance of the fabric. From macro scale to micro scale, fabric texture properties include color, shape, and directionality at two levels of materials, i.e., yarn and fiber materials. The color and shape of yarn and fiber materials are considered as the two most important factors in fabric texture images. Another important characteristic of the fabric texture is the distributing trait of material directions, i.e. the directionality of yarn material and fiber material.

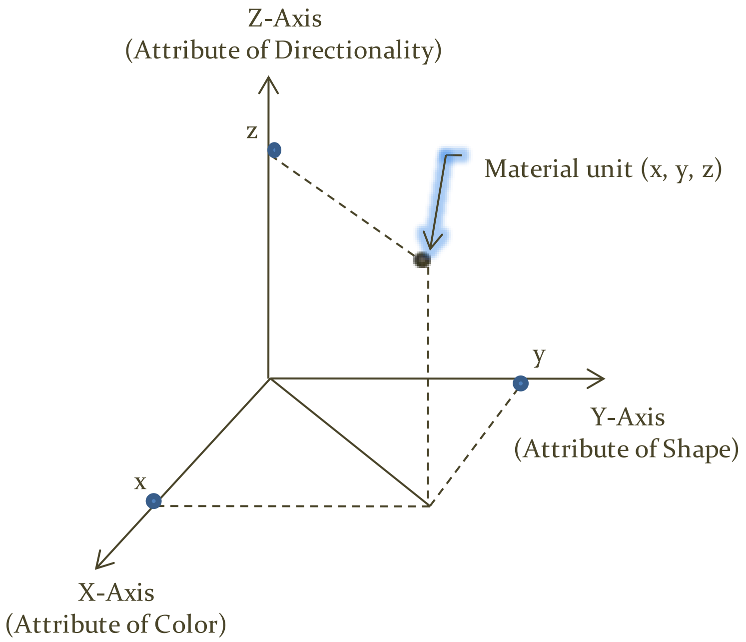


Figure 4. Three-dimensional coordinate system of texture properties.

There is a layered relation between fabric texture properties and material attributes as shown in Figure 3. Fabric consists of yarns and fibers, so-called basic material units in the process of fabric texture design. Each material unit is represented by a three-dimensional vector of attributes, i.e. the color of material, shape of material and directionality of material. As shown in Figure 4, fabric texture properties will be determined by three attributes of material units in the three-dimensional coordinate.

There are six independent dimensions for the two types of material units, yarn and fiber. The parameters of texture properties can be described by the three-dimensional coordinate of texture properties. At the fiber level, they are:

(Fiber color - X, fiber thickness - Y, fiber length - Y, fiber arrangement directionality→ yarn twist / yarn density - Z),

and at the yarn level, they are:

(Yarn color - X, yarn thickness - Y, yarn float length -Y, yarn arrangement directionality→yarn layout / fabric density - Z),

where each technical parameter is followed by an attribute in the three-dimensional texture coordinate, i.e. - X, - Y, or – Z. "Or" relationship is represented by sign /. The sign → is used to represent that the corresponding material parameters in the process of fabric texture design and production can be derived from an attribute in the three-dimensional texture coordinate. Note that the arrangement directionality of material units is used to describe the main feature of alignment of material units, such as yarn and fiber.

The appearance of a fabric texture is mainly determined by the parameters of material unit. In some cases, finishing plays an important role in affecting the fabric texture properties. The fabric texture properties created by the finishing function can be described by the parameters of material unit in a fabric texture image. When the texture properties are not suitable to be described by the individual material parameter or parameters, the statistical texture features introduced in [95] may help to describe the essential texture properties generated by finishing. As an example, brushing is a popular method to generate hairiness on the surface of a fabric. Instead of using material attributes in the three-dimensional texture coordinate, it is convenient to describe the characteristics of the fabric texture by the global chaotic statistical features. In fact, the example can be considered as a special case as the material units are not divided into yarn materials and fiber materials but are thought as the whole units of fiber and yarn.

The foregoing analysis shows that fabric texture properties are based on two types of material units, yarn and fiber. The texture properties of fabric images can be described by three attributes of the material units. Material unit-based texture attribute analysis is to identify, appraise, select and synthesize fabric texture parameters. The parameters to describe fabric texture properties are defined by the attributes of material units at the yarn level or fiber level. For different parameters of a fabric texture, an appropriate attribute in the three-dimensional texture coordinate is used to represent the parameter.

3.3.2 OAR model for fabric texture properties analysis

The OAR model is a powerful tool to the fabric texture properties analysis, in which objects, attributes and relations are defined as a triple. As described in section 3.1, the development of a complete OAR model includes the developments of A and R for the fabric texture properties analysis. The O is fabric texture images. A is the set of attributes to describe fabric texture properties, which is defined by Equation (3). Each feature vector in Equation (3) can be described by one or more material attributes in the three-dimensional texture coordinate. In this section, the focus is to develop R.

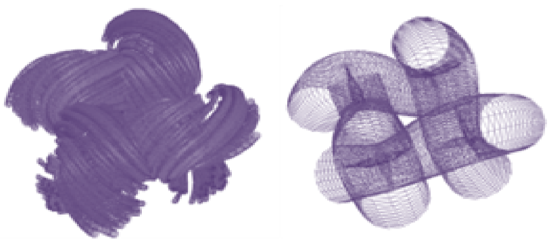


Figure 5. 3D properties of fabric texture surface.

There are many parameters to describe the fabric texture properties at the yarn and fiber material units. The essential relation R in the OAR model for the fabric texture properties analysis is to find a function that describes a mapping between fabric texture images and fabric texture parameters. The purposes of finding such a mapping function are: (1) to reduce the number of dimensions of the fabric texture image, (2) describe material parameters as computable features by machine, and (3) sort, group and merge features to differentiate fabric texture images.

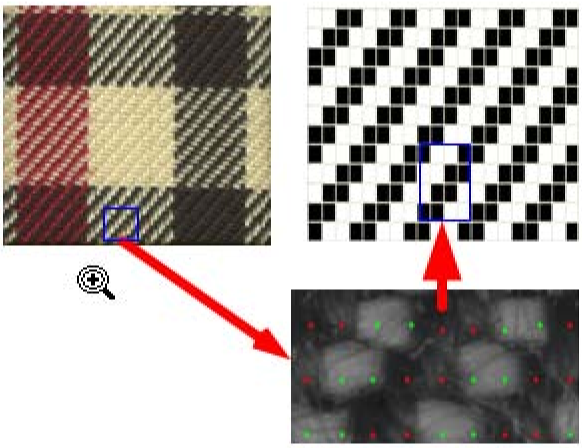


Figure 6. Fabric and weave pattern R[s].

The parameters of fabric texture properties are defined by the material attributes in the three-dimensional texture coordinate. There is another aspect to be defined for a fabric texture, i.e., how to organize the material units of yarn and fiber. As shown in Figure 5 [96], there is an interlacing structure, the so-called R in terms of structure (R[s]). R[s] represents a 3D interlacing structure of material units in which the locations of yarn materials and fiber materials are defined in a three-dimensional space. At each interlacing area of yarn materials, the directionality of fiber materials categorizes the yarn materials into two types: warp and weft. Other material parameters are included in the material units at the yarn level or fiber level, such as color and thickness. Since the fabric is made only by interlacing the warp yarns in a vertical direction and the weft yarns in a horizontal direction, there are two exact states at each crossing point of warp and weft. That is, the warp is interlaced over the weft or vice versa. The former is called a warp point and the latter weft point.

Given the colorway layouts in both horizontal and vertical directions, the appearance of the fabric texture depends mainly on the yarn interlacing status. Colorway layout refers to the spatial arrangement of yarn materials in a two-dimension space. In Figure 6, a fabric with three colorways in warp (red, yellow and black) and two colorways in weft (black and yellow) has a twill interlacing pattern. The number of grid lines in a horizontal direction is equal to the number of weft yarn material units and the locations of grid lines indicate the locations of the weft yarn material units. Similarly, the number of warp yarn material units and their locations are defined by the grid system.

The interlacing structure of material units is represented by the black and white cells in the grid system. The black cells are used to indicate warp points and white cells to represent the weft points. Thus, the spatial organization of material units is represented by R[s] in a grid system. The appearance of a fabric depends primarily on R[s] and its cell properties, such as color and crossing state yarn material units. Material parameters can be encoded into properties of cells in the grid system. The properties of cells are represented by the attributes in the three-dimensional texture coordinate and the data structure of the properties of cells is a hierarchical system in a table form.

3.3.3 Development of fabric texture fingerprints

There exist two levels of material units in a fabric and it is necessary to use two levels of imaging resolutions in the fabric digitization process. The high resolution imaging method is used to digitize the fabric texture details at the fiber level. The parameters of fiber material properties, such as fiber color and thickness, can be examined in the high resolution fabric image. The low resolution of imaging method is used for capturing the fabric texture properties at the yarn level. The parameters of yarn material units, such as yarn color and thickness, can be evaluated in the low resolution fabric image.

As shown in the cognitive informatics model developed in section 3.3, the texture fingerprints in the image layer are used to connect the physical fabric texture to the abstract concepts, attributes and relations in the internal world of texture operations. The texture fingerprint is developed according to three aspects: material units which are detailed in 3.3.1, R[s] that is the essential map to describe fabric material features, and imaging resolution that depends on the material units. Thus, fabric texture fingerprints can be described by material units, material features in R[s], and fabric texture images:

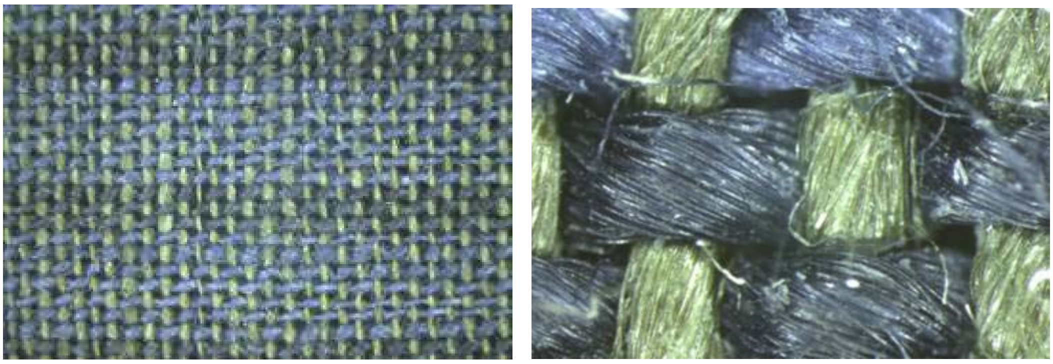
$$T \mathrel{\hat{=}} (M, F, I) \tag{4}$$

where T is the fabric texture fingerprints. I is the image of a fabric texture, e.g., a JPEG format file. F is the material feature vectors for fabric texture operations. M is the material unit.

In a fabric texture, there are two types of material units, fiber and yarn, as described in Section 3.3.1. The target of development of F in Equation (4) is to find the minimal number of material features that can uniquely determine the material units in the fabric texture. The development of fabric texture fingerprints for given material units and their texture images in T includes two aspects, as described below:

(1) Definition of F. Each material feature is defined according to the material production parameter, namely fabric density, yarn thickness, color layout, and yarn interlacing status.

(2) Optimization of F. For the near regular fabric texture, essential material features can be defined through observations from experiments. For chaotic fabric textures, essential material features can be defined by user feedback investigation, such as the relations reconfiguring scheme in Section 3.2.



(a) (b)

Figure 7. Fabric texture images with different material details. (a) yarn-level image. (b) fiber-level image.

Two levels of imaging resolutions are used to observe fabric material units. An example of a fabric texture is shown in Figure 7. The properties of fiber material units can be observed in the fabric texture image on the right in Figure 7 wherein I = high resolution JPEG file and M = fiber material units. Based on the observations of high resolution images of the fabric texture, the fabric texture fingerprint at M =fiber is developed as:

Ff = ($f1$: input from users, including the number of colors and regions of sample colors in the image; $f2$: locations and sizes of fiber clusters; $f3$: fibers directionality) (5)

where $f1$ is used to understand the user's observation. $f2$ can determine yarn density, yarn thickness, and color layout. $f3$ can determine yarn interlacing status. $f2$ and $f3$, thus, will uniquely determine fabric texture properties at the fiber level. The directionality of fiber materials is defined by using the definition of texture directionality in [97].

When I =low resolution JPEG file, the fabric texture image is shown on the left in Figure 7. The fabric texture fingerprint at M =yarn is developed as:

Fy = ($f1$: the grid system in R[s]; $f2$: location and size of texel, $f3$: symmetry representation) (6)

where $f1$, $f2$ and $f3$ will uniquely determine the texel fingerprints of the fabric texture when M =yarn. A texel, or texture element, is the fundamental unit of texture space. The texel of fabric pattern refers to the most prominent repeat pattern of fabric texture at yarn material units. Yarn level fingerprints are thus defined by the location and size of texel. The grid system in R[s] and symmetry representation are used to characterize the arrangement of texels in the fabric weaving network.

3.4 Summary

In this chapter, I established a framework to study fabric texture properties through an interdisciplinary approach. An OAR model is presented for fabric texture analysis. The OAR model points out the major cognitive features to be searched and classified in the process of fabric design. The model provides guidance to fabric texture digitization, analysis and operations. A cognitive informatics model for fabric texture operations is thus proposed based on the OAR model, in which a relation between high-level features / concepts and low-level features is built through fingerprints of fabric material units.

To facilitate fabric texture search and classification by major attributes, two levels of fabric texture fingerprints are developed based on the fabric OAR model and the cognitive informatics model for fabric texture operations. The essential features of fabric texture fingerprints are captured using two levels of imaging resolutions, i.e. the high resolution for the fiber material units and low resolution for yarn material units. This chapter provides a general research framework for a fabric database management system, based on which fabric texture operations are conducted, including fabric search, pattern classification and texture synthesis.

Chapter 4:

Weave Pattern Search

The proliferation of digital capture devices and the explosive growth of community-contributed media contents have led to a surge of research activity in fabric image search or retrieval. Text-based image search systems have been deployed by main stream search engines such as Google, Yahoo, as well as Microsoft. Although the research on content-based image search has existed for decades, it seems that there are few practical systems of content-based image search which can be commercialized [98].

This research introduces cognitive models for fabric texture analysis and operations in Chapter 3. The further analysis of fabric texture properties in Section 3.3 reveals that texture fingerprints are connections between object concepts and attributes of texture properties. Based on the development of fabric texture fingerprints in Section 3.3.3, fabric texture analysis and operations techniques for fabric pattern search will be detailed in this chapter.

4.1 Attributes representation

Object-attribute-relation (OAR) model explains how information or knowledge is represented in LTM and the model is described as a triple in which A is a finite set of attributes to define object characteristics or properties. An attribute can be the accurate quantitative term to define texture material parameter or the general qualitative form to describe the appearance. In Section 3.1, A in the OAR model is represented by three aspects of texture-based properties and their detailed properties will be individually developed for fabric texture in the following sections.

4.1.1 Material structure complexity

Woven fabrics are highly structured materials, having their appearance, handling and mechanical properties influenced by their geometric structure. Fabric pattern has a basic unit of weave for production that is periodically repeated throughout the entire fabric network. The basic unit is called weave pattern R[s] for fabric pattern production. The material network is formed based on the weave pattern format during the production process. Designer selects weave patterns according to the weave pattern complexity and then determines the weaving parameters of the machine accordingly.

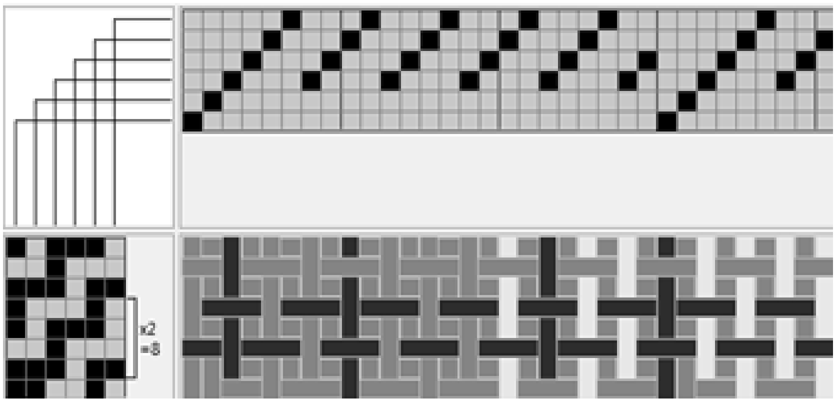


Figure 8. The drafting plan of weave pattern on loom.

There is a well established format for representing the weave pattern known as WIF (Weave Information File) format for industrial production usage. As illustrated in Figure 8, a weave pattern has three parts: warp yarn setup (bottom right, controlled by warping machine), weft yarn setup (bottom left, controlled by weft shuttle, also named as peg plan code in textile mills) and tie-up (upper part, also named drafting in textile mills). The pattern of a fabric product is generated by the above three parts, so it can be treated as an encoding process of fabric pattern production.

Extraction of the control point of yarn path is as follows, from the tie-up plan section of WIF file:

$$\varepsilon(\partial,\Gamma)=\mu(\zeta(\Gamma),\zeta(\partial)) \tag{7}$$

where $\zeta(\Gamma)\in\{1,...,m_1\}$ is the weave encoding function for weft yarns (m_1 is the number of weft threading). $\zeta(\partial)\in\{1,...,m_2\}$ is the weave encoding function for warp yarns (m_2 is the number of warp threading). μ is the function described in the tie-up plan section. WIF contains the threading information that defines the threading of the warp yarns into the heddles of the shafts. It also contains a lift plan which represents the combination of shafts raised for creation of each weft. The weave pattern is obtained by combining the threading and the lift plan information. Weave pattern search by complexity becomes:

$$P_c=P(\zeta) \tag{8}$$

where P is the prioritization function to evaluate the information complexity (energy function) of weave pattern. It is noteworthy that the weave pattern information is compressed through Equation (7) which is related to the complexity of weave pattern and is a representation of material-based organizational structure as well. In this section, an indexing method is used as a prioritization function to prioritize the complexity of production code (peg plan code) for fabric weave pattern.

To reveal the fundamental information of the weave patterns, a mathematical method is thus needed to compress and then index these patterns. The concept of information is too broad to be captured by a single definition. Luckily, for any probability distribution, a quantity called entropy can be defined, which has many properties that agree with the intuitive notion of what a measure of information should be. The initial questions treated by information theory lay in the areas of data compression and transmission; entropy is interpreted as the ultimate data compression [99]. Data compression can be achieved by assigning short descriptions to the most frequent outcomes of the data source, and necessarily longer descriptions to the less frequent outcomes. Entropy is a function of the probability distributions that underlie the process of data compression and communication. For a discrete source X, the self-information of symbol x_i which occurs with probability p_{x_i} is defined as $I_{x_i} = -\log_m p_{x_i}$. The uncertainty or entropy of the source is defined as:

$$H(X) = E(I_X) = -\sum_i p_{x_i} \log_m p_{x_i} \tag{9}$$

where $H(X)$ is the average information per source output. The base of the log function is 2 ($m = 2$) and entropy is expressed in bits. It is related to the distribution of source probability. The concept of entropy I in information theory is related to the concept of entropy in statistical mechanics. The entropy arises in statistical mechanics as a measure of uncertainty or disorganization in a physical system. The entropy can be regarded as the logarithm of the number of ways in which the physical system can be configured. Information-theoretic quantities such as entropy arise again and again as the answer to the fundamental questions in communication and statistics. The entropy concept is used in this study to represent the weave pattern information in the process of fabric pattern production.

The entropy of a random variable is a measure of the random variable; it is a measure of the amount of information required on the average to describe the random variable. Indeed, the weave pattern diagram can be treated as an image of point distributions in black and white. As a very abstract representation, weave pattern diagram is used by a textile designer to deal with texture designs that contain the amount of information of yarn interlacing points and their statistics meanings. In a weave pattern diagram, the distribution of different brightness intensities can be read by a weaving machine to produce the corresponding woven structure in which the interlacing rules of material units will be determined. The characteristics of fabric woven textures are then represented by interlacing rules of material units in a fabric weave pattern diagram. The entropy of the weave pattern diagram will be different from each other for its corresponding woven texture. It is possible to describe the weave pattern diagram by its entropy to measure the material network complexity in a fabric.

Given an image, the size is $M \times N$ and function $f(x, y)$ represents the brightness distribution of pixels. If $f(x, y) = \{k_1, k_2, \cdots k_L\}$ and the probability of brightness intensity in the image is $p_f = \{p_1, p_2, \cdots, p_L\}$, the information entropy from Equation (9) for the weave pattern image can be given as:

$$H_L(p_1, p_2, \cdots, p_L) = -\sum_{i=1}^{L} p_i \log_2 p_i \tag{10}$$

As introduced in previous sections, the interlacing status for material units at yarn level only includes two situations, i.e. weft point and warp point. The former is denoted as white ($f(x,y)=0$) and the latter denoted as black ($f(x,y)=1$) in a weave pattern image. In this case, Equation (9) becomes:

$$H_2(p_0,p_1) = -p_0\log_2 p_0 - p_1\log_2 p_1 \tag{11}$$

$$p_1 = \sum_M\sum_N \frac{f(x,y)}{M\times N},\ p_0 = 1 - p_1 \tag{12}$$

The calculation of material network complexity for a fabric involves the microscopic essence of the pattern complexity based on the probability of occurrence for each weft or warp yarn point. However, in a weave pattern image, entropy cannot describe the spatial distribution of weft and warp points and the distance of different distributions with the same number of weft and warp points. For example, theoretically, weave pattern simple plain weave and basket plain weave have the same entropy value, but they have different number of weft and warp points in spatial domain. In allusion to this shortcoming, Fast Fourier Transform (FFT) is used to extract the information of spatial distribution of yarn interlacing points.

For the discrete case, the corresponding pair of the two-dimensional Fourier transform of an image is:

$$F(u,v) = \frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)\exp(-j2\pi(\frac{ux}{M}+\frac{vy}{N})),$$

$$u = 0,1,2,...M-1,\ v = 0,1,2,...N-1 \tag{13}$$

$$f(x,y) = \frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} F(u,v)\exp(j2\pi(\frac{ux}{M}+\frac{vy}{N})),$$

$$x = 0,1,2,...M-1,\ y = 0,1,2,...N-1 \tag{14}$$

The formulation in (13) and (14) can reduce N^2 operations in the DFT to

$N \log_2 N$ operations in the FFT. The basic idea of the FFT is that the DFT of N elements is the sum of the DFTs of two subsets: even-numbered points and odd-numbered points. The dataset can be recursively split into even and odd until the length equals one.

The Fourier transformed domain of the image is filtered so as to select those frequency components deemed to be of interest to a particular application, e.g. fabric density calculation and even pattern recognition or classification [60]. Alternatively, it is convenient to collect the magnitude transform data in achieve a reduced set of measurements. The FFT data can be normalized by the sum of the squared values of each magnitude component, so that the magnitude data is invariant to linear shifts to obtain normalized Fourier coefficients NF as:

$$NF_{u,v} = \frac{\left|F_{u,v}\right|}{\sqrt{\sum_{(u \neq 0) \wedge (v \neq 0)} \left|F_{u,v}\right|^2}} \tag{15}$$

Histogram equalization can provide such invariance, but it is more complicated than using Equation (15) in terms of computation cost. The spectral data can be described by the entropy as:

$$H(F(u,v)) = \sum_{u=1}^{M} \sum_{v=1}^{N} NF_{u,v} \log_2 (NF_{u,v}) \tag{16}$$

where $H(F(u,v))$ is called the spectral data entropy or FFT Entropy.

4.1.2 Structural appearance

The appearance of the weave pattern of a fabric is highly related to the organizational structures of material units in horizontal and vertical directions. In this section, an orientation-based cognitive approach is proposed to index the structural appearance in weave patterns.

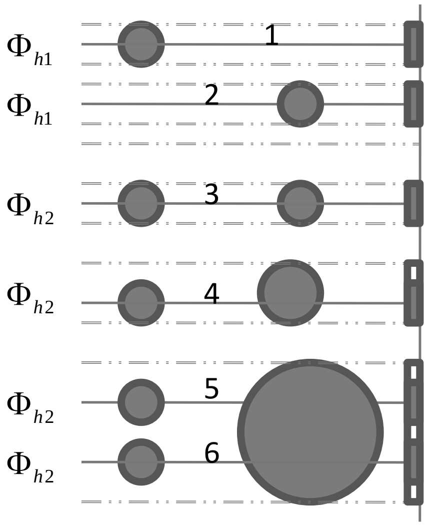


Figure 9. Spatial relationship of objects.

An orientation-based score can be used to scale the regularity of pattern arrangement according to human beings adaptive visual perception in the context of weave pattern design. The subjective criteria for grouping weave patterns are highly related to the regularity measurement of the distributions of the objects of interest. In this section, an objective orientation-based measurement of pattern distribution is developed. In this way weave pattern appearance is evaluated and indexed by the regularity of the distributions of objects in horizontal and vertical directions.

Table 3. Distance measurement value for scattering patterns

ID	SCA1	SCA2	SCA3	SCA4	SCA5	SCA6
SCA1	0	2	3.5	5	4	5
SCA2	2	0	1.5	3	2	3
SCA3	3.5	1.5	0	1.5	2.5	1.5
SCA4	5	3	1.5	0	3	4.5
SCA5	4	2	2.5	3	0	3

SCA6	5	3	1.5	4.5	3	0

A difficult content-based pattern problem is thought as a simple directional analysis problem (horizontal and vertical) according to fabric material production alignments in two directions, weft and warp directions. The “node” and “trail” are defined in this study to represent the objects of interest in the weave pattern and their spatial relationship in a line. Specifically, there are vertical trails and horizontal trails. Note that the trail here is not a yarn but a virtual line to describe the spatial relationship of objects (nodes) in a direction. Intuitively, the calculation method can be considered as a grouping process in which the nodes are grouped by threads that have a connection function.

As shown in Figure 9, if the horizontal projections of the nodes on vertical axis have intersection part, the nodes are defined on the same trail. There are two directions of threads, horizontal trail Ψ_h and vertical trail Ψ_v. In each trail direction, there are different types of trails. Each trail type is determined by the number of nodes on the trail. The horizontal trail Ψ_h and vertical trail Ψ_v are given by:

$$\Psi_h = \{\Gamma_{h \cdot i}(\alpha)\}, \Psi_v = \{\Gamma_{v \cdot i}(\alpha)\}, i = 1, 2, \dots n \tag{17}$$

where i is the index number of trail type. As illustrated in Figure 10, the trail type is defined by the number of nodes on the trail. h indicates horizontal direction and v indicates vertical direction. n is the number of trail types. α is the number of objects on each trail. The trail type $\Gamma_{h \cdot i}(\alpha)$ is represented by:

$$\Gamma_{h \cdot i}(\alpha) = \alpha, i = \alpha \tag{18}$$

where the index value of trail type is the number of nodes on the trail.

The load value of the nodes on a trail is given by, for example, in horizontal:

$$\Phi_{hi} = 1 + (\Gamma_{h \cdot \alpha}(\alpha) - 1) \cdot \chi$$

$$i \in \{0, 1, 2, 3, ..., l\} \tag{19}$$

where χ is a weight, l is the number of the trails in the pattern and a is the number of nodes on each trail. For instance, if take $\chi = 0.5$, the value of Φ_{h0}, Φ_{h1}, Φ_{h2}, Φ_{h3} in Figure 10 is 0, 1, 1.5, 2.5, respectively. The difference of load value between trail type 0 and 1 is larger than 1 and 2. The distance measurement of load value maps the concept that the question of object existing or not is more important than the difference of numbers in terms of human pattern perception and understanding.

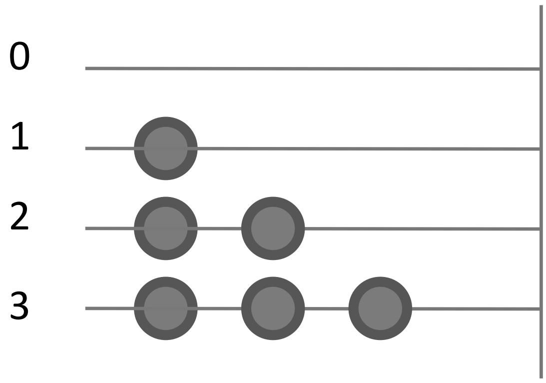


Figure 10. Different trail types.

The mass center spatial position and size of objects in a two-dimensional coordinate plane may introduce different spatial relationships as shown in Figure 9. The nodes on the same trail are defined by:

$$P_{h \to v} \cap Q_{h \to v} \neq 0 \tag{20}$$

where $P_{h \to v}$ and $Q_{h \to v}$ are the horizontal projections of object P and Q on vertical axis. The nodes are defined on the same trail when horizontal projections of the nodes have intersection part on vertical axis. Similarly, the single vertical trail type can be defined. In Figure 9, the property of threads 5 and 6 is different from others. It is proposed to differentiate the property by using private trail and public trail. The public trail is defined as:

$$(P_{h\to v} \cap T_{h\to v}) \cap (T_{h\to v} \cap Q_{h\to v}) = 0,$$

$$P_{h\to v} \cap T_{h\to v} \neq 0, T_{h\to v} \cap Q_{h\to v} \neq 0. \tag{21}$$

where $T_{h\to v}$ is the horizontal projection of object T on vertical axis. In Figure 9, threads 1, 2, 3, 4 are private threads and Trail 5 and 6 are public threads. The load value of private trail is calculated by Equation (19) and public trail is described as:

$$\Theta_{hi} = \sum_{1}^{n} \Phi_{hi} - \delta \cdot (n-1) \tag{22}$$

where n is the number of threads which are public trail type and δ is a weight. The Distance Measurement of Trail-Node (DM-Trail-Node) is given by

$$\mathrm{M} = \sum_{i}^{U} | \Phi_{h\cdot\alpha(1i)}(\alpha) - \Phi_{h\cdot\alpha(2i)}(\alpha) | + \sum_{i}^{V} | \Theta_{h\cdot\alpha(1i)}(\alpha) - \Theta_{h\cdot\alpha(2i)}(\alpha) |$$

$$+ \sum_{i}^{P} | \Phi_{v\cdot\alpha(1i)}(\alpha) - \Phi_{v\cdot\alpha(2i)}(\alpha) | + \sum_{i}^{Q} | \Theta_{v\cdot\alpha(1i)}(\alpha) - \Theta_{v\cdot\alpha(2i)}(\alpha) | \tag{23}$$

where U is the number of private threads and V is the number of public threads in horizontal direction. P is the number of private threads and Q is the number of public threads in vertical direction. The nearest index of threads is calculated in pairs.

Six examples of scattering patterns are given in Figure 11. The corresponding distance measurement (DM-Trail-Node) values are shown in

Table 3. The distance measurement can describe the spatial distribution difference in terms of object directional distribution (horizontal and vertical) and the number of objects of scattering patterns. For example, the distance value of SCA4-SCA5 is larger than SCA4-SCA3. In Figure 12, there is a triangle spatial distribution with vertical trail in SCA3 and SCA4. There is a triangle spatial distribution with both horizontal and vertical threads in SCA5. The distance between SCA3 and SCA4 is considered to be smaller in Figure 12.

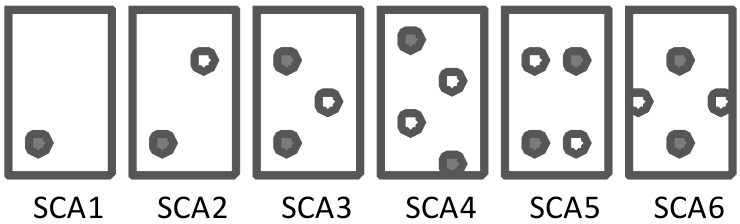


Figure 11. Examples of patterns.

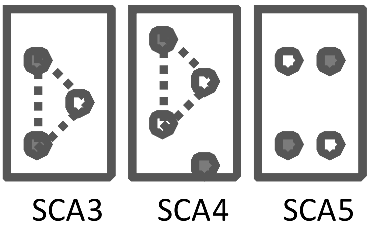


Figure 12. Object distributions of examples.

In the proposed trail-node spatial descriptor, the spatial distribution relationship is defined by different types of trail. It is a three dimensional feature vector (direction; attributes of trail; trail category). The direction includes horizontal and vertical. The attributes of trail has two types: private attribute and public attribute. The trail category is determined by the number of nodes on a trail. The total number of features is $2*2*\alpha$. The distance measurement is calculated by DM-Trail-Node.

4.1.3 Cognitive repetition features

A weave pattern design can be examined from two aspects: texel and repetition. Texel refers to the most obvious texture element in the fabric texture, which is considered to be the fundamental or essential unit of a fabric design. When the stimuli of texel patterns are repeated, the neural activity is usually reduced which is referred to as adaption. The components of a weave pattern design are perceived and understood when repetition suppression happens. Thus, texel and repetition characterization are the two important cognitive features for weave pattern design.

Texel and repetition can be adopted as cognitive features to prioritize weave patterns. For example, the size of texel and the number of repetitions in a fabric texture can be used to index and search fabric patterns. A method proposed in [88] was adopted to detect deformed texels in an image. In fabric design, texel and repetition are detected by the underlying fact that the fabric material units are arranged in a grid system. The detection steps are conducted as follows:

First, Harris corner detector [100] is adopted to detect low-level cues as the most obvious features to track in a fabric image. The Harris corner detector is based on an underlying assumption that corners are associated with maxima of the local autocorrelation function. It is less sensitive to noise in the image than most other algorithms, because the computations are based entirely on first derivatives and it has high reliability in finding L junctions and good temporal stability [101]. Weave pattern textures may contain defects and local small texture details which are not essential for human beings understanding of weave pattern composition (texture element and repetition). In this regard, Harris corner detector is suitable to analyze low-level texture features in a fabric image.

Second, clustering techniques are then used to cluster interest points by image patch appearance. Mean-shift clustering technique is adopted. The repetition directionality is perfectly constrained along warp and weft direction. The proposed repetition structure is thus simplified as a tiling problem of rectangular elements. There are no obvious geometrical occlusions and deformations. In each detected feature point cluster, three points are randomly selected and are calculated by the affine transformation that maps the grid structure feature vector [(0, 0), (0, 1), (1, 0)]. The best proposal of the repetition basis comes out from multiple random selections and is determined by the largest number of votes on the supporting grid structures.

Third, an inferring algorithm is used to find the similar structure points in the underlying grid system of a fabric image. In practice, the weave pattern may contain small defects and material deformations. The underlying grid system in a fabric image is not a perfect grid structure. A tracking mechanism is needed for grid expansion. Given its efficiency, the MSBP algorithm is chosen for refining texel locations [88]. A MRF model is a choice for inferring texture element locations with two constrained functions. The first is the joint compatibility function which is given by:

$$\wp(x_{[i,j]}, T_{[i,j]}) = \exp(-\alpha(1 - T_{[i,j]})) \tag{24}$$

where $x_{[i,j]}$ is the 2D coordinate of texel node (the position of the node), α is a constant that is set empirically, and $T_{[i,j]}$ is an image patch likelihood which is computed by normalized cross correlation between the grid candidate patch and the proposed grid template.

The second kind of function for the MRF is the pairwise compatibility function. The spatial constraints between neighboring pairs of texture elements are defined below:

$$\varphi(x_{[i,j]}, x_{[i,j\pm1]}) = \exp(-\beta \times h(x_{[i,j]}, x_{[i,j\pm1]})^2),$$

$$\varphi(x_{[i,j]}, x_{[i\pm1,j]}) = \exp(-\beta \times v(x_{[i,j]}, x_{[i\pm1,j]})^2) \tag{25}$$

where h and v is the spatial consistency of the pair of elements, and β is a constant that is set empirically. The spatial consistency function is defined by the normalized error term:

$$NE(t_1^i, t_2^i, t_1^j, t_2^j,) = \max(\|t_1^i - t_1^j\| / \|t_1^i\|, \|t_2^i - t_2^j\| / \|t_2^i\|) \tag{26}$$

The *region of dominance* is introduced to determine if an estimated texture element location can be trusted. The current estimated location with local maxima dominant peak is chosen as a peak location to determine the location of the trusted texture elements. The trusted texture elements are considered as the most obvious texels in the fabric image. The number of detected texture elements is defined as the number of repetitions of a pattern in the fabric image.

4.2 Feature representation

Fabric texture fingerprints have been developed in Section 3.3.3 and fingerprints representations of two material units have been given in Equation (5) and (6). Among these features in fabric fingerprint representations, two essential features in F of Equation (4): yarn location detection and crossing structure recognition will be detailed in this section. The two features determine weave pattern complexity defined in Section 4.1.1. The organization of this section is as follows.

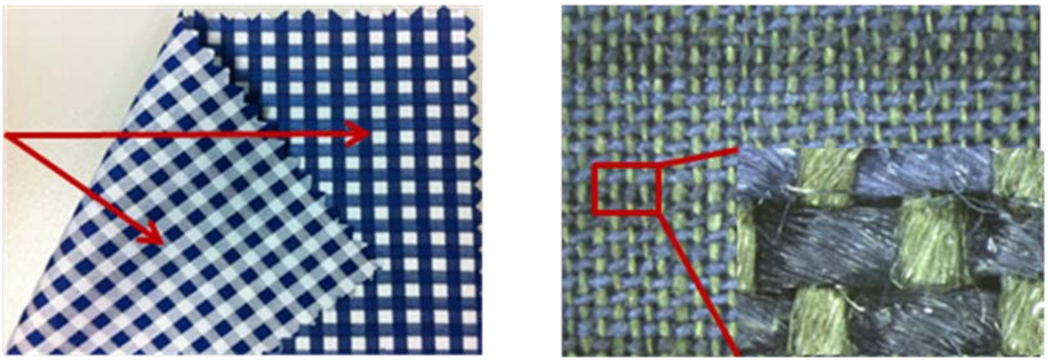
First, the fabric texture digitization methods are discussed. Second, the fabric weave pattern recognition problem is formulated as a structure orientation identification problem that simultaneously detects the yarn location as well as the yarn crossing structure in a woven fabric. A new local orientation pattern feature is proposed for fabric structure detection using high resolution images.

The research method comprises two main steps. First, the yarn location is detected by using a series of the image enhancement techniques and the yarn intensity projection method. Alternatively, an interactive yarn detection method is also introduced to process fabric textures with complex surface appearance or captured by a low-resolution imaging method. Second, the fabric structure is then recognized with a local orientation detection approach based on Radon transform.

4.2.1 Imaging methodology

As described in Section 3.3.1, each material unit in the three-dimensional texture coordinate has its corresponding texture attributes. A systematic review of fabric texture properties reveals that the texture attributes of material units are analyzed from high resolution images and low resolution images. Therefore, choosing an appropriate imaging methodology is indispensible.

There are two different perspectives to imaging a fabric texture: (1) focusing on the same material unit with different imaging conditions, and (2) capturing different material units with similar imaging conditions. Since fabric texture may cover a spectrum going from stochastic to regular, it presents computational challenges for state of the art fabric pattern search. Investigation of fabric imaging conditions is necessary in order to be able to compare or integrate fabric texture data from different measurements.



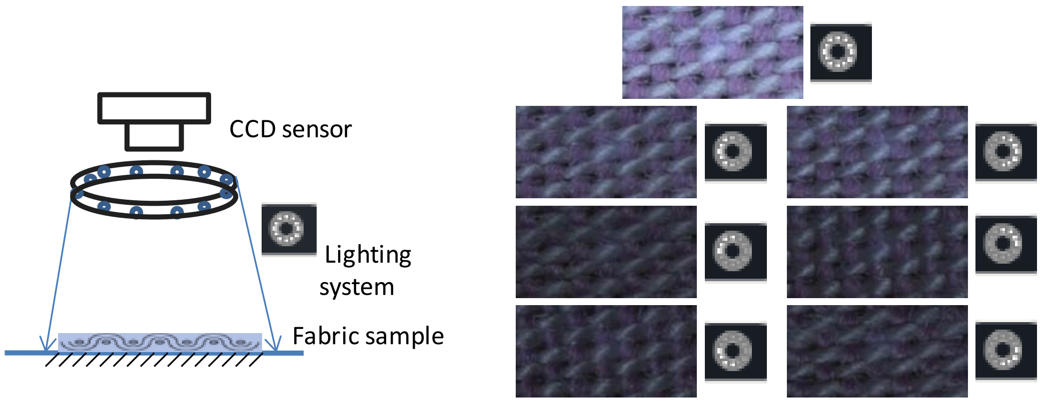
(a) (b)

Figure 13. Imaging methods of fabric texture appearance. (a) face and back side. (b) macro and micro scale.

The commonality behind the varied appearance of fabric textures is their strong tendency towards regularity or symmetry, even though the regularity is often imperfectly presented and intertwined with stochastic signals and random noise. The random noise of a fabric texture, such as distortion and hairiness, is produced in the process of manufacturing. To obtain the comprehensive texture information, multiple images of a fabric texture at different levels are desired.

There are two important imaging techniques for fabric texture digitization. The first technique is to capture the surface appearance with multiple images of texture areas on the face and back side of the fabric texture, as shown in Figure 13 (a). The second technique is to capture local and global regions of the fabric appearances with different scales as shown in Figure 13 (b). Therefore, these imaging techniques should be useful to faithfully record the multi-level surface appearances of fabric swatches. For fabric texture browsing, it should be noted that the texture appearance can be observed and identified by an experienced technologist, as shown in Figure 13. However, these images may not be adequate for texture feature extraction by machine.

In the experiment, the high resolution image of the yarn-dyed cotton fabric is captured by the Leica M165c imaging acquisition system. As shown in Figure 14, in order to generate different lighting conditions for testing, the uniform lighting conditions and the directional lighting conditions are generated by adjusting the LED lighting system. The lighting system is mounted above the fabric sample and each LED light can be controlled to adjust the illumination conditions.



(a) (b)

Figure 14. The imaging acquisition system. (a) the position of the LED lighting system. (b) different lighting conditions.

The fabric reflective image is captured by a CCD sensor of Leica M165c. The image resolution for the physical fabric size in the experiment is around 560 pixels per millimeter. That is, one millimeter of the real fabric corresponds to 560 pixels in the fabric image.

4.2.2 Location detection

The finished fabric products can be of almost any color, shape, and texture. This section introduces two types of location detection ways: (1) an automatic method for high resolution fabric images; and (2) an interactive method for fabric patterns captured in low-resolution images.

4.2.2.1 Automatic location detection

Wavelet transform can be employed to transform the digitized spatial image into the image based on space-frequency domain [28, 29]. It integrates the regional and global characteristics and provides a powerful signal treatment function in many fields, such as texture segmentation and edge detection. In the segmentation of warp and weft yarns, wavelet transform can be selected to enhance the image along the warp and weft directions.

The Wavelet transform is given by:

$$f(t) = \sum_{j \in z} \sum_{k \in z} c(j,k) \Psi_{j,k}(t) \tag{27}$$

where

$$f(t) = \left\langle \Psi_{j,k}(t), \Psi_{m,n}(t) \right\rangle = 0, \; j \neq k, m \neq n \tag{28}$$

$$c(j,k) = \left\langle f(t), \Psi_{j,k}(t) \right\rangle \tag{29}$$

where $f(t)$ is the original signal, $c(j,k)$ is the coefficient matrix, and $\Psi_{m,n}(t)$ is the j th layer frequency of Wavelet transform. As for the Wavelet function at the location k, Equation (28) shows that the inner product of any two functions with a different basis must be 0 in terms of the orthogonal Wavelet transform. Accordingly, in Equation (29), the coefficient $c(j,k)$ is obtained from the original signal and the inner product of the basis.

The base used in this study is Haar Wavelet (db1) [102] that is a ladder-shaped discontinuous function and is suitable for the inspection of products of speedy manufacture. Since the woven fabric consists of warp and weft yarns in the horizontal and vertical directions, it is desired to enhance the yarn signals by the signal decomposition graph of Wavelet transform in terms of horizontal and vertical high frequency signals. The high frequency signals represent the yarn edge signals of warp and weft floats in the original fabric image.

The projection method [26, 74, 103, 104] was used to detect the yarn location in previous work. In a surface reflection fabric image, the yarns have higher intensity values while the interstices between yarns have lower intensity values. The underlying square grid structure of yarns in woven fabric allows us to analyze yarn locations by two directions in the image. The projection profile on the gray-level values along weft and warp directions can be calculated by:

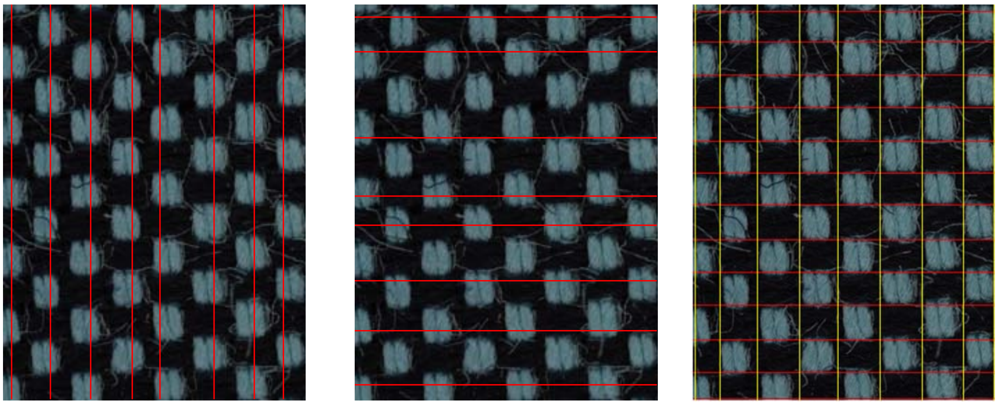
$$L(y) = \frac{1}{N}\sum_{x=0}^{N-1} f(x, y)$$

$$L(x) = \frac{1}{M}\sum_{y=0}^{M-1} f(x, y) \tag{30}$$

where, $f(x, y)$ is the gray-level value of a pixel. N and M is the number of pixels in weft and warp direction.

Since the fabric image may contain both the signal noise and the yarn hariness, the performance of the method is mainly depended on two image processing techniques: the image enhancing technique and the shadow intensity extraction. In this study, the Coherence Enhancing Diffusion (CED) technique is adopted to enhance the coherence of the flow-like fiber orientation structures in the structural reflection image [105].

On the other hand, Wavelet transform is then applied to extract the shadows or edges along the warp and weft floats. By using the image intensity projection method in warp and weft directions [74], the 1D spatial accumulation distribution of the yarn and the interstices projection profile is obtained. Furthermore, before applying the peak detection technique, Moving Average (MA) filter [106] is used to reduce the random noise while keep the sharpest step edge response in the projection signals.

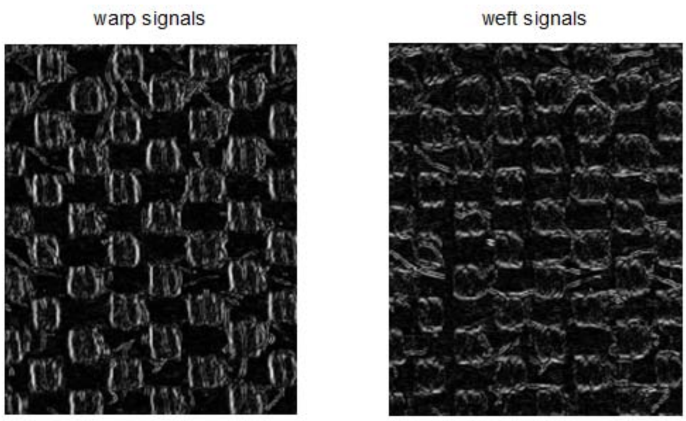


(a) (b) (c)

Figure 15. The yarn location detection results. (a) warp yarn location detection result by the traditional method. (b) weft yarn location detection result by the traditional method. (c) detection results of yarn locations by the proposed method.

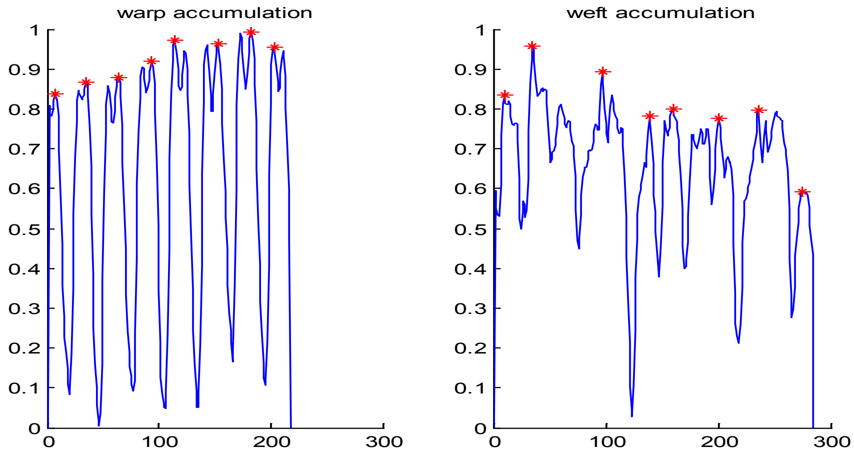
The traditional gray-projection method may not be suitable for detecting the yarn-dyed fabric including dark color yarns [74]. Figure 15 shows the yarn location detection results by the traditional method in warp and weft directions. The results show that there are misjudgments of the weft yarn locations. Furthermore, the yarn locations of both the warp and weft yarns are not detected accurately. Hence, it is infeasible to use the locations of the yarns by the traditional gray-projection method to recognize the fabric structure and the weave pattern.

In this study, Wavelet transform is used to extract the yarn information along warp and weft directions. The first layer frequency of Wavelet transform is selected to analyze the warp and weft yarn signals. The base used in the experiment is the Haar Wavelet (db1). As shown in Figure 16, the high frequency details of Wavelet transform decomposition in the vertical and horizontal directions can provide useful information for yarn location analysis. When the yarn float is warp, the boundary of the float is enhanced along the warp direction. Similarly, the weft float is enhanced along the weft direction.

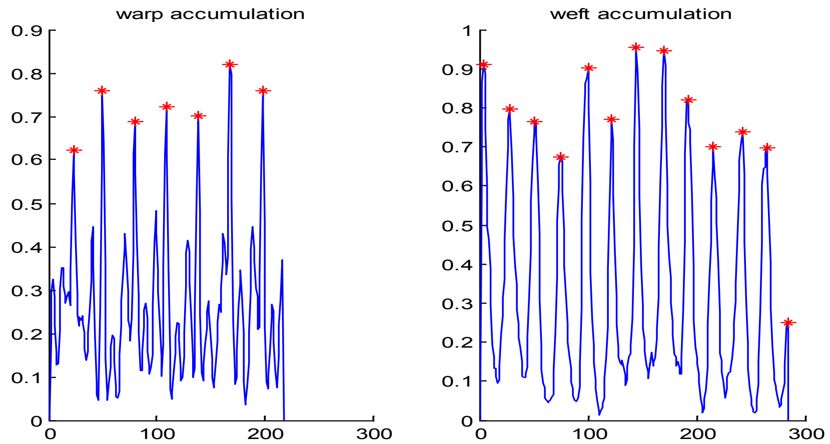


(a) (b)

Figure 16. The extraction results of warp and weft signals by Wavelet transform. (a) the warp yarn signals extraction result. (b) the weft yarn signals extraction result.



(a) (b)



(c) (d)

Figure 17. The projected yarn signals and the detected yarn locations. (a) the warp detection result of the traditional gray-projection method. (b) the weft detection result of the traditional gray-projection method. (c) the warp detection result of the proposed method. (d) the weft detection result of the proposed method.

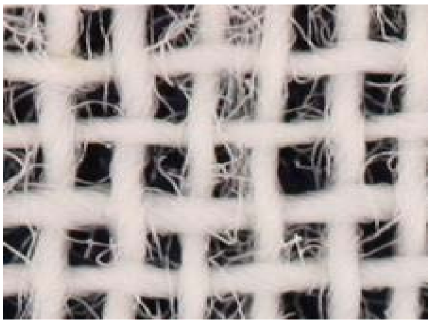
The projection signals of the yarns and their interstices by the traditional gray-projection method and the proposed method are shown in Figure 17. The stars on the projection curve are the peak values detected by the methods. The values of the horizontal axis in the warp accumulation curve are the horizontal locations in the image and the values of the horizontal axis in the weft accumulation curve are the vertical locations in the image. The detection results of the Wavelet transform decomposition projection method are shown in Figure

15 (c). It can be seen that good results of yarn location detection are obtained by using the proposed yarn detection method. In order to test the proposed method, more experimental results of different samples will be shown in Section 4.2.3.

4.2.2.2 Interactive location detection

In this study, more than 5000 fabric samples are collected to investigate fabric texture characteristics. Different texture characteristics present problems that can be solved by different algorithms. It is difficult to find an algorithm that is fully automated for yarn location detection. Four examples from the collections are shown in Figure 18. For more examples of fabric textures, see Appendix A. It can be seen that the assumption of the projection method do not hold for all fabrics in the testing dataset. Further, to illustrate the richness of the characteristics of fabric textures, different techniques are tested and the results are shown from Figure 19 to Figure 22.

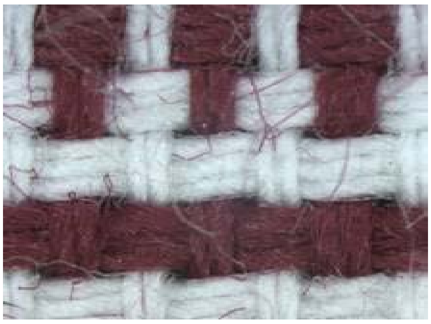
Projections of weft yarn in horizontal direction and warp yarn in vertical direction are calculated. There are eight calculations as shown in Figure 19. For each sample, there are two groups of material units, warp yarns and weft yarns. Each row in Figure 19 illustrates two calculations for a fabric image. The peaks and valleys in both warp and weft directions are relatively easy to detect for samples of (a) and (b) with low densities of yarn material units. Sample (c) is a solid-color texture and the densities of yarn material units are high in both warp and weft directions. Since the density of weft direction is lower than warp direction in Sample (c), the detection of peaks or valleys are also easier in weft direction than in warp direction. Sample (d) is a color-patterned texture with high densities of material units. The texture patterns of weft direction are more various than warp direction. There are five clusters of weft projection intensities and two clusters of warp projection intensities. Therefore, the locations of warp yarn material units are relatively easy to detect. However, the weft yarn location detection is a challenge. As a result, it can be concluded that the accuracy of yarn location detection is influenced by the combined effects of color patterns and the densities of fabrics in fabric textures.



(a)

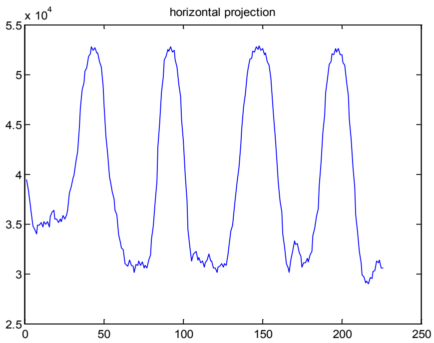
(b)

(c)

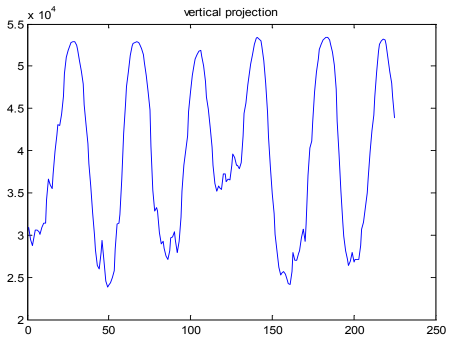


(d)

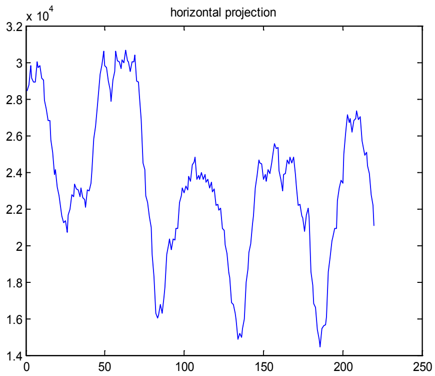
Figure 18. Examples of fabric texture collection. (a) solid color sample with low density. (b) multi color sample with irregular yarn size. (c) solid color sample with high density. (d) multi color sample with indistinct yarn edges.


horizontal projection
x 10^4
5.5
5
4.5
4
3.5
3
2.5
0
50
100
150
200
250

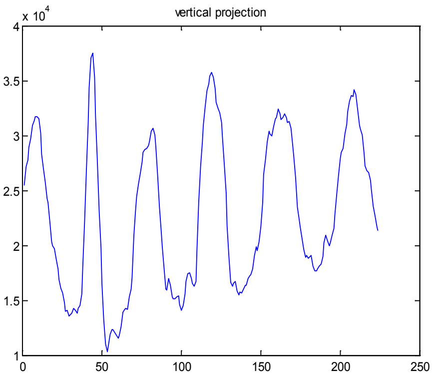
(a)


vertical projection
x 10^4
5.5
5
4.5
4
3.5
3
2.5
2
0
50
100
150
200
250

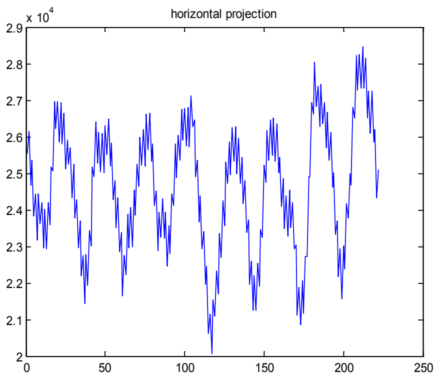
(b)


horizontal projection
x 10^4
3.2
3
2.8
2.6
2.4
2.2
2
1.8
1.6
1.4
0
50
100
150
200
250

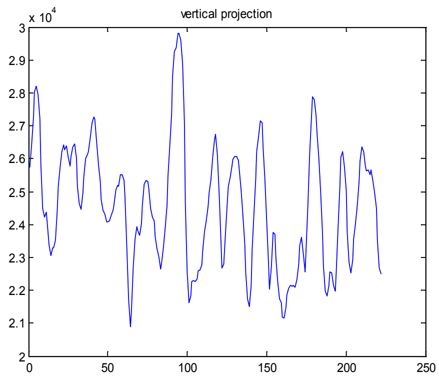
(c)


vertical projection
x 10^4
4
3.5
3
2.5
2
1.5
1
0
50
100
150
200
250

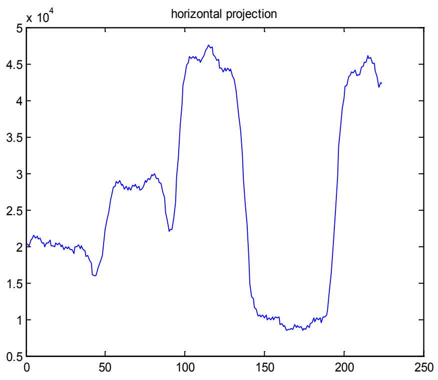
(d)


horizontal projection
x 10^4
2.9
2.8
2.7
2.6
2.5
2.4
2.3
2.2
2.1
2
0
50
100
150
200
250

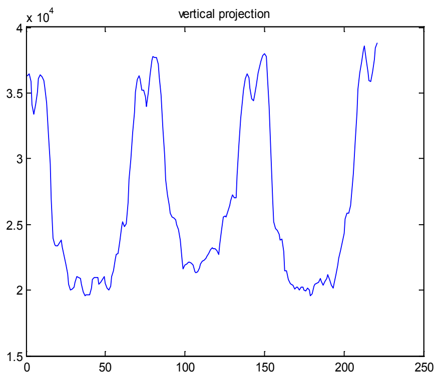
(e)


vertical projection
x 10^4
3
2.9
2.8
2.7
2.6
2.5
2.4
2.3
2.2
2.1
2
0
50
100
150
200
250

(f)

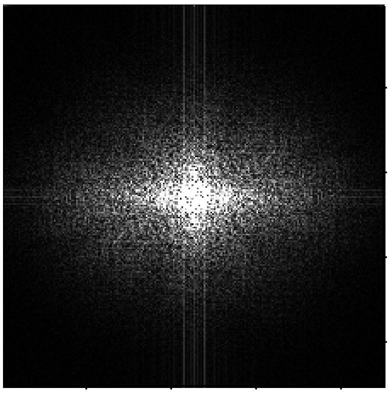


(g)

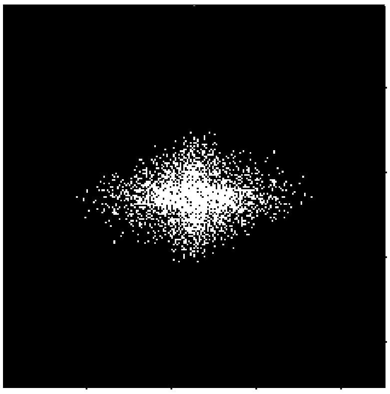


(h)

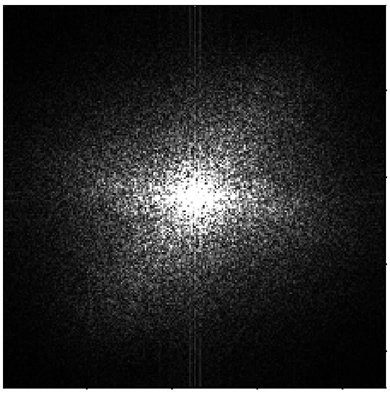
Figure 19. Method I in Section 4.2.2.1. (a) weft projection for Sample (a) in Figure 18. (b) warp projection for Sample (a) in Figure 18. (a) weft projection for Sample (b) in Figure 18. (b) warp projection for Sample (b) in Figure 18. (a) weft projection for Sample (c) in Figure 18. (b) warp projection for Sample (c) in Figure 18. (a) weft projection for Sample (d) in Figure 18. (b) warp projection for Sample (d) in Figure 18.



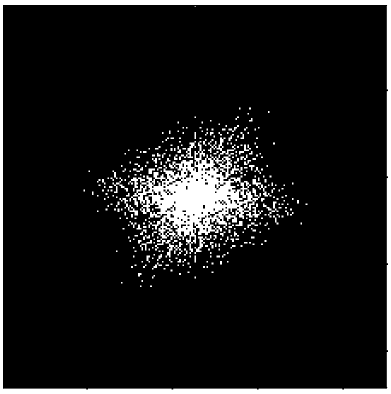
(a)



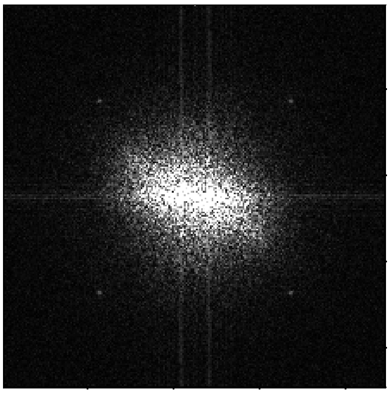
(b)

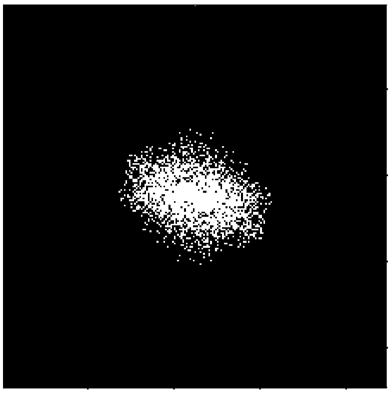


(c)

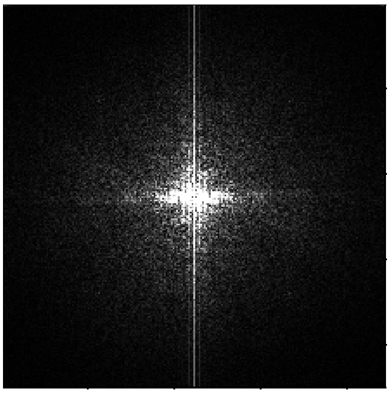


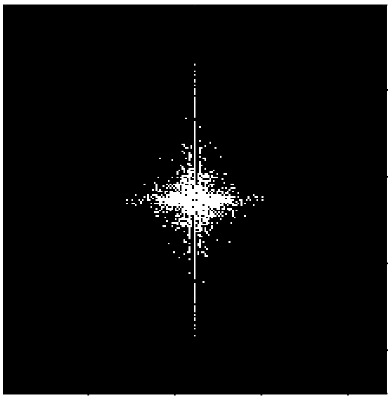
(d)





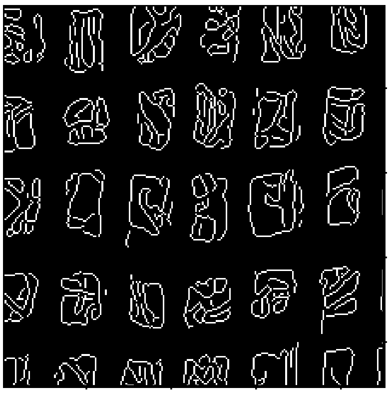
(e) (f)

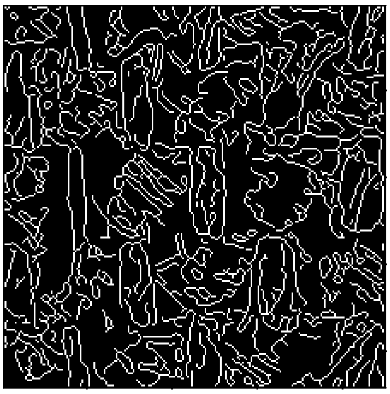




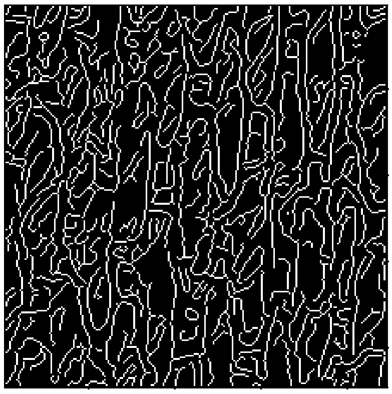
(g) (h)

Figure 20. Method II power spectrum of FFT. (a) power spectrum for Sample (a) in Figure 18. (b) power spectrum with threshold for Sample (a) in Figure 18. (c) power spectrum for Sample (b) in Figure 18. (d) power spectrum with threshold for Sample (b) in Figure 18. (e) power spectrum for Sample (c) in Figure 18. (f) power spectrum with threshold for Sample (c) in Figure 18. (g) power spectrum for Sample (d) in Figure 18. (h) power spectrum with threshold for Sample (d) in Figure 18.

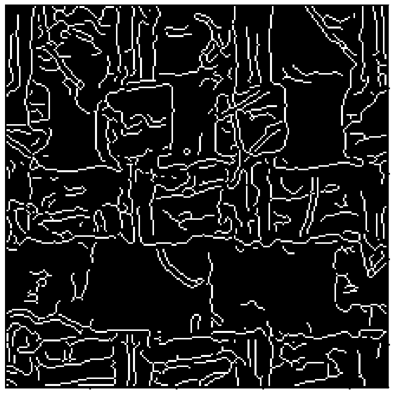




(a) (b)

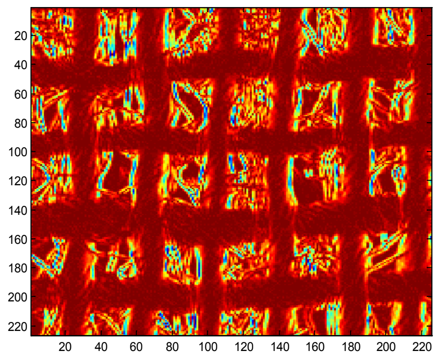


©

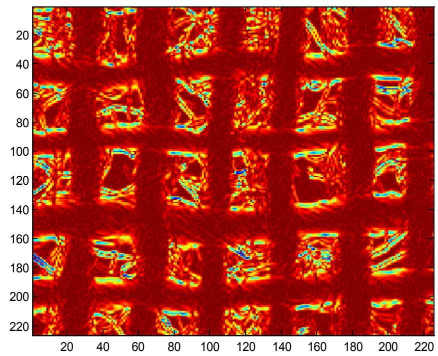


(d)

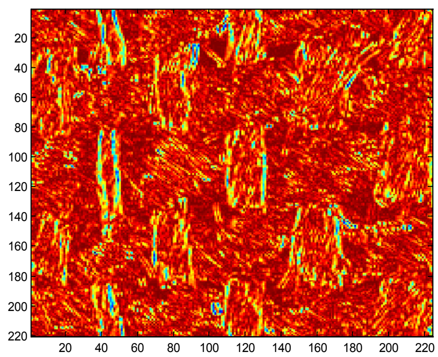
Figure 21. Method III edge detection by Canny algorithm. (a) edge detection result for Sample (a) in Figure 18. (b) edge detection result for Sample (b) in Figure 18. (c) edge detection result for Sample (c) in Figure 18. (d) edge detection result for Sample (d) in Figure 18.



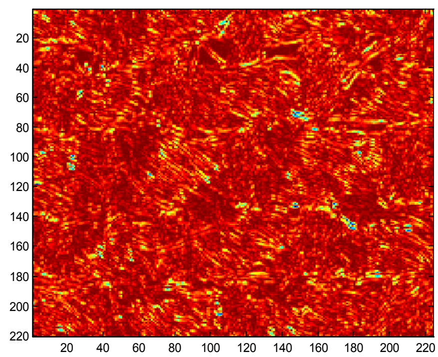
(a)



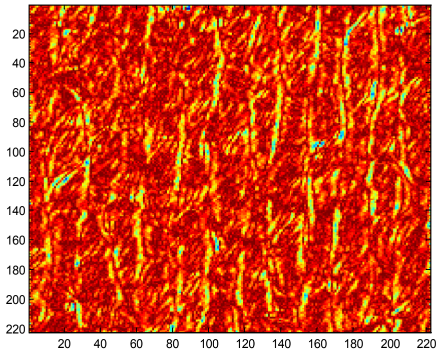
(b)



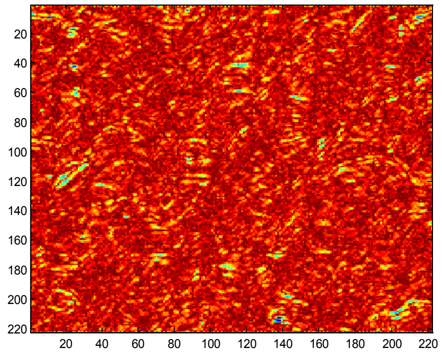
(c)



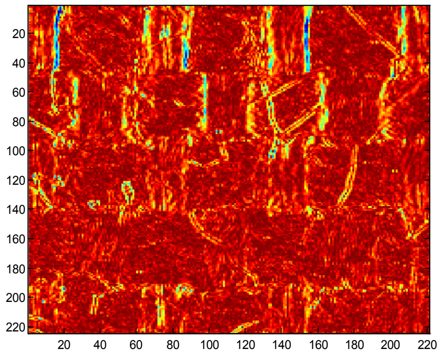
(d)



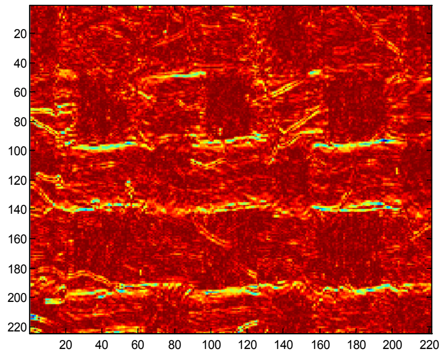
(e)



(f)



(g)



(h)

Figure 22. Method IV gradient map of yarn edge. (a) warp gradient map for Sample (a) in Figure 18. (b) weft gradient map for Sample (a) in Figure 18. (c) warp gradient map for Sample (b) in Figure 18. (d) weft gradient map for Sample (b) in Figure 18. (e) warp gradient map for Sample (c) in Figure 18. (f) weft gradient map for Sample (c) in Figure 18. (g) warp gradient map for Sample (d) in Figure 18. (h) weft gradient map for Sample (d) in Figure 18.

Next, other analysis techniques are also tested for these samples. Fast Fourier Transform (FFT) is applied to analyze the locations of yarn material units by the periodic light intensity of yarns in fabric images. In Figure 20, power spectrum of FFT for each texture image is calculated. The results indicate that low frequency components (sharp shadows, edges, and hairiness) and high frequency components (smooth colored regions) of the projection curves are difficult to discriminate due to irregularity of material shape and orientation, for example Sample (d). Therefore, both noise of hairiness and variation of colors of yarns in the texture image make the periodicity of yarn materials difficult to be selected out from the power spectrum.

Since edge is the basic feature to describe an object in a vision detection system, the edge locations of yarns are the most straightforward features to detect yarns in a fabric image. In this study, Canny algorithm has been used to extract the edges of objects in a fabric image. Sample (a) has low density both in warp and weft. In this case, the edges of yarns can be extracted easiliy based on the Canny algorithm. However, the method would fail to extract edges of yarns in fabrics with high density, such as for samples of (b), (c) and (d), as shown in Figure 21 (b), (c) and (d). Thus, the calculations reveal little correspondence between locations of yarns in the original images and locations of edges in the edge maps.

Gradient map of fabric texture is also calculated in horizontal and vertical directions. The calculations are shown in Figure 22. One of the drawbacks of gradient distribution is that the method cannot extract global variations of material units in terms of color and region. The results of Method III and Method IV are similar. Cues from gradient map are helpful to locate yarns for Sample (a). Similar to Method III, gradient maps of Sample (b), (c) and (d) provide little useful information to detect locations of yarns. Yarn location detection techniques based on color or texture segmentation are not investigated since they provide poor segmentation results for fabric images with solid color and fuzzy texture. For instance, yarn locations of Sample (c) are difficult to extract by color or texture segmentation techniques.

In the four methods tested, method I performs better than the rest as it captures the essence of fabric material production. The underlying structure of warp and weft materials is approximately a grid structure. Method I introduced in 4.2.2.1 is simple and straightforward to explain material locations in the fabric image. The projection results of brightness intensity have good correlation with human perception. Nevertheless, the method also has encountered situations and problems that are not readily soluble in some cases, such as fabrics with high density. In practice, to overcome the difficulties in the automatic detection method, an interactive method, i.e. the computer assisted analysis method, is then proposed for yarn location in woven fabric images.

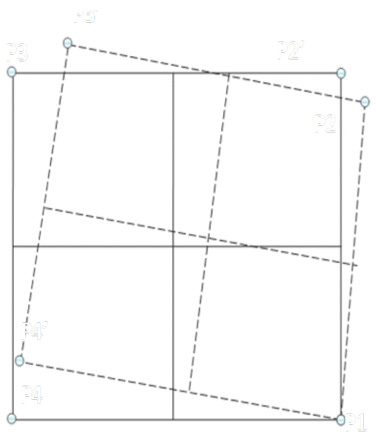


Figure 23. Lattice of yarn interlacing location.

For any woven fabric texture wp, four neighboring interlacing points of warp and weft yarns are taken. There exists an underlying lattice L that is a geometrical distortion of a square lattice L_s. Vertices of L_s correspond to the points with integer coordinates, x-coordinates being in the range 1,..., n, y-coordinates being in the range 1,...m. n is the number of warp yarns and m is the number of weft yarns. Two vertices are connected by an edge wherein the corresponding points are at distance 1. As shown in Figure 23, two vertically adjacent warp yarns and two horizontally adjacent weft yarns are defined as the basic lattice of yarn interlacing locations. The geometric deformation field d_{geo} is defined as a function that maps L to L_s and the deformation distance between them has been discussed in [90, 107]. In [10], user-assisted lattice extraction was developed to model the geometrical deformation of a near-regular texture. In the same way, yarn locations with a 4-cyle grid graph are specified.

The process of specifying yarn interlacing locations in a fabric image is as follows:

Step I. The user specifies the initial yarn interlacing locations by clicking three neighboring points of warp and weft yarns on a fabric image wp to suggest a pair of lattice generating vectors, $\vec{t}_1, \vec{t}_2$, as shown in Figure 24 (a);

Step II. Based on the given lattice locations, the computer generates uniform lattices on the input fabric wp with the same vector generators, $\vec{t}_1, \vec{t}_2$, as shown in Figure 24 (b);

Step III. The computer compares the automatic location detection results of Section 4.2.2.1 with the user specified lattice location and suggests possible modifications, as shown in Figure 24 (c);

Step IV. The user adjusts some of the misplaced interlacing points of yarns to generate L on the computer screen. As illustrated in Figure 25, the user may click a lattice edge to select the whole line in red or yellow to rotate the line (left image) or shift its locations (middle image). Red line is the weft yarn axis and yellow is the warp. Local adjustment of individual lattice is carried out by dragging each lattice point on the computer screen (right image). User can also add or remove a line from the existing lines by double-clicking and deleting it;

Step V. The computer saves the lines user modified as L_s. The number of red and yellow lines in L_s is the number of yarns in the fabric image. The locations of lines indicate the axes of yarn material units in the fabric image.

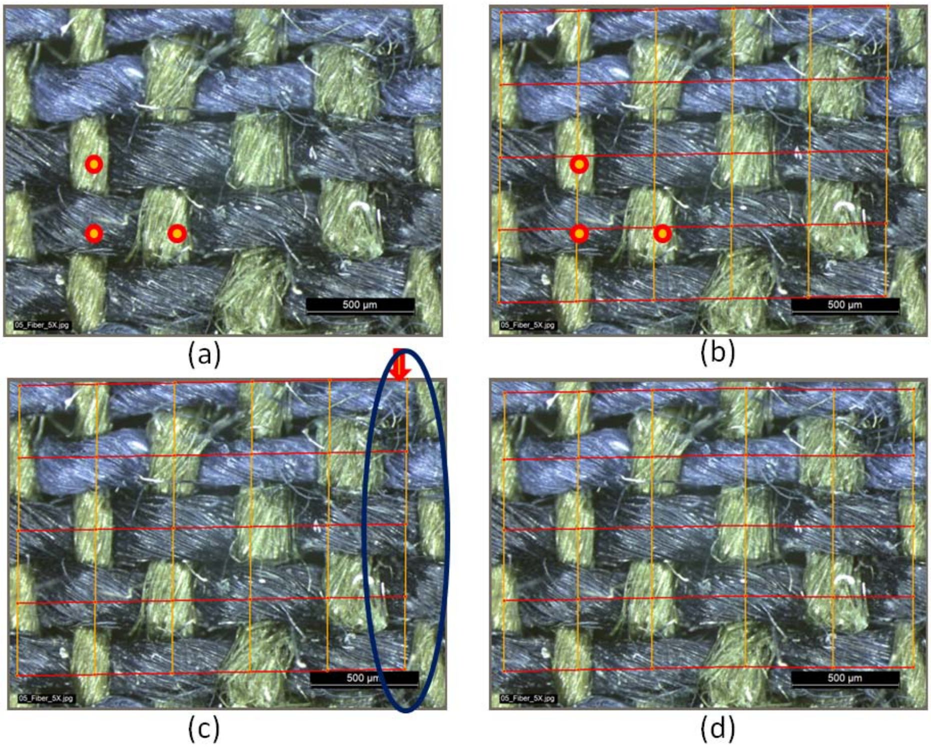


Figure 24. Interactive yarn location detection. (a) specifying the initial yarn interlacing points. (b) generating the grid. (c) correcting the locations of nodes of the grid. (d) final locations of the nodes of the grid.

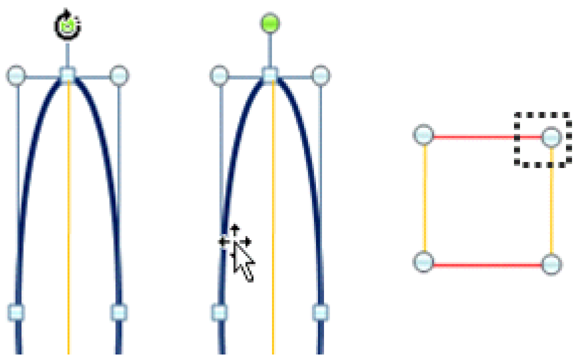


Figure 25. Operations of adjustment.

4.2.3 Structure recognition

In this section, a interlacing point recognition method for yarns in the fabric as well as the experiment results are presented and discussed in detail. As described in the previous section, the yarn floats are located by the grid of the lines simultaneously when the locations of the yarn interstices are detected. For each yarn segment, the fiber orientation can be used as the key feature to discriminate the warp yarns and the weft yarns as discussed in Section 3.3.3 of Chapter 3. Therefore, the detection of the weave pattern of a woven fabric is to detection the fiber orientation in the yarns of the fabric image.

Once the locations of the yarns in the fabric have been detected, the crossing points of the warp and weft then can be possibly recognized according to the yarn interlacing status. There are two groups of yarns in woven fabric and the fiber orientation of the yarn floats can be used as the statistical texture feature to classify the yarns with the orientation angles. In this study, Radon transform is used to detect the fiber orientation in the yarn floats and thus determine the fabric structure and the weave pattern.

The Radon transform computes the projections of an image along the specified directions. The transform is given by:

$$R_\theta(\rho) = \int_{-\infty}^{+\infty} f(x'\cos\theta - y'\sin\theta, x'\sin\theta + y'\cos\theta)dy' \tag{31}$$

where

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \tag{32}$$

Equation (31) and (32) transform the spatial domain image $f(x, y)$ into the corresponding projection domain image defined by θ and ρ, where θ is the angle of the projection of the image intensity and ρ is the smallest distance to the origin of the coordinate system. The illustration of Radon transform is shown in Figure 26.

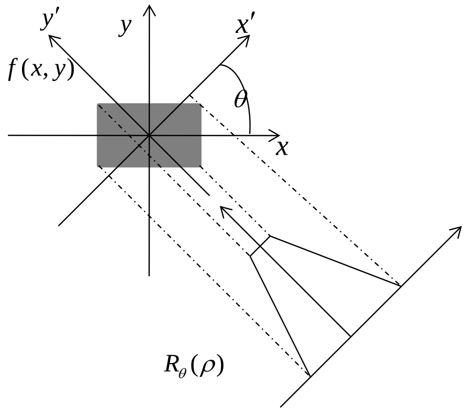


Figure 26. Illustration of Radon transform.

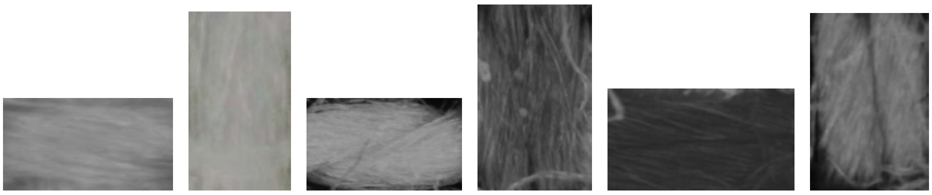
Radon transform generates a signature composed of 180 values, one for each angle in the range of $[0° - 179°]$ in $1°$ increments. Each value sums up the size of the image components that are shaped along the given angle. Therefore, Radon transform can be used to detect the fiber orientation in the yarn segments.

The yarn floats patches are extracted from the yarn location grid and the fiber orientation of warp floats is different from that of weft floats. As shown in Figure 27, the fibers in warp floats are laid around vertical direction and the fibers in weft around horizontal direction. Radon transform is used to detect the fiber orientation of the yarn floats. In the experiment, the membership function of the fiber orientation corresponding to the warp or the weft yarn float can be defined as follows:

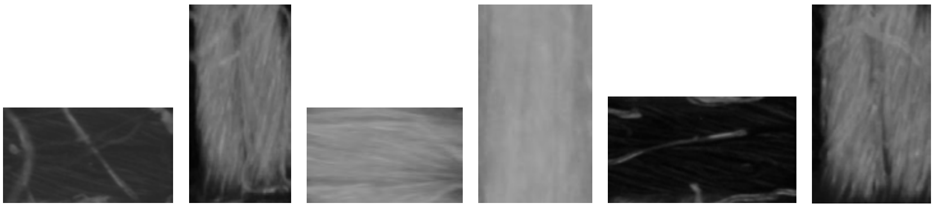
$$\begin{aligned} &\theta\_Warp = \left\{\theta \,|\, \left|\theta - 90°\right| < \varepsilon\right\}, \theta \in [0, 179°) \\ &\theta\_Weft = \left\{\theta \,|\, \left|\theta - 90°\right| \geq \varepsilon\right\}, \theta \in [0, 179°) \end{aligned} \tag{33}$$

where θ is the fiber orientation angle that is detected by Radon transform. Empirically, take $\varepsilon = 30°$ in all calculations in this paper.

Figure 27 shows that some of the yarn floats may be very difficult to detect even for human eye due to the fuzziness of the micro structures in light or dark colors and the presence of the yarn hariness, for example (b) and (g). On the other hand, both the ratio of the yarn float width and length and the shape of the yarn float patch are also various and irregular, as shown in Figure 28, which makes that it is difficult to detect the types of the yarn floats by its shape. Hence, the key of the fabric structure recognition is to find a more suitable feature to describe the material organization essence in the fabric structure.



(a) (b) (c) (d) (e) (f)

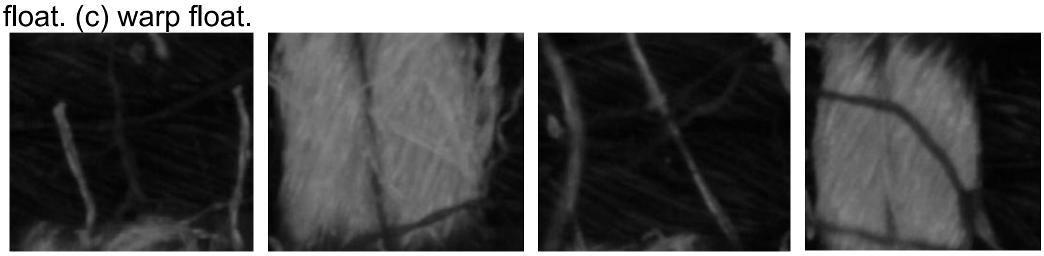


(g) (h) (i) (j) (k) (l)

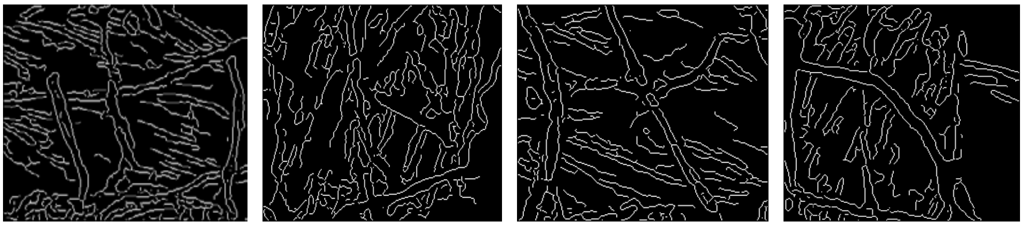
Figure 27. Examples of the yarn floats from the fabric samples. (a), (c), (e), (g), (i)and (k) are weft floats. (b), (d), (f), (h), (j) and (l) are warp floats.

(a) (b) (c)

Figure 28. Examples of the shape of the yarn float patch. (a) weft float. (b) weft float. (c) warp float.

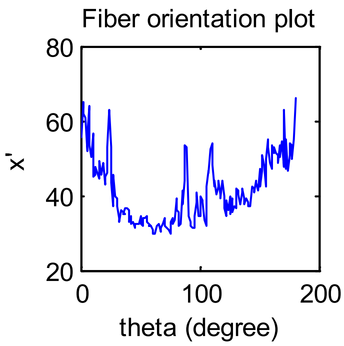


(a) (b) (c) (d)

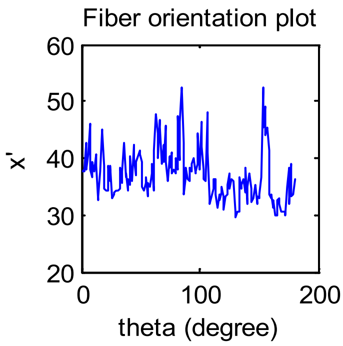


(e) (f) (g) (h)

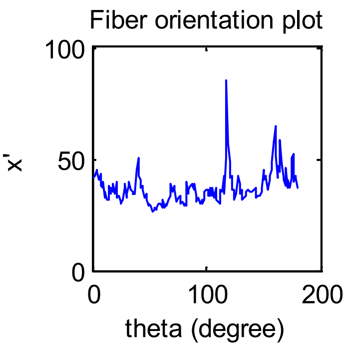
Figure 29. Yarn hariness on the yarn float patch. (a) weft float patch. (b) warp float patch. (c) weft float patch. (d) warp float patch. (e) the edge map for the Sample (a). (f) the edge map for Sample (b). (g) the edge map for Sample (c). (h) the edge map for Sample (d).



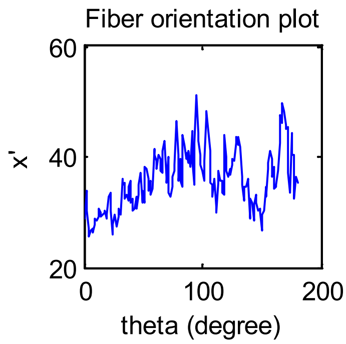
(a)



(b)



(c)



(d)

Figure 30. (a) the fiber orientation distribution plot for Sample (a). (b) the fiber orientation distribution plot for Sample (b). (c) the fiber orientation distribution plot Sample for (c). (d) the fiber orientation distribution plot for Sample (d).

The fiber orientation feature is based on the yarn layout in the fabric structural organization that can be considered to be the key feature to determine the yarn float type. From the high resolution images of yarn floats, it can be seen that the edges of the yarn floats are not very clear. However, the fiber orientation is relatively consistent along a certain direction. In the perceptions of the professional fabric designers, the continuity of the fiber orientation is also the key texture feature that leads to the cognition of yarn floats discrimination.

In the experiments, the hairiness on the yarn floats may have an influence on the orientation detection of the whole float patch. Four examples of the yarn floats are shown in (a), (b), (c) and (d) in Figure 29. The corresponding edge maps obtained from the Canny algorithm and the fiber orientation plots calculated by Radon transform are given in (e), (f), (g), (h) of Figure 29, and (a), (b), (c), (d) of Figure 30, respectively.

From the fiber orientation plots, it can be seen that it is dangerous to use either the largest orientation response or the dominant orientation responses as the final orientation angle or angles to determine the yarn float type. In this study, the top k largest responses are used as the candidates to classify the yarn float type. In all tests in the experiment, the 20% of the largest orientation responses in Radon transform are taken, i.e. k =180*20%.

For the given yarn float patches, a classification function is used to differ the warp floats from weft floats according to the fiber orientation angles. The classification function is composed of two sub functions: the membership function of the fiber orientation as given in Equation (33) and the voting function. The voting function is defined to form the final judgment of the yarn float type, which is given by:

$$\begin{aligned} D &= 1, when\ L_1 \geq L_2 + 1 \\ D &= 0, when\ L_1 < L_2 + 1 \end{aligned} \tag{34}$$

where $D = 1$ means the fiber patch is the warp patch. In the similar way, $D = 0$ represents the weft patch. L_1 is the statistical number of the warp memberships in the top k orientation responses in Random transform and L_2 the statistical number of the weft memberships in the top k responses.

Luckily, Sample (a), (b) and (c) in Figure 30 are detected by the classification function as the weft float ($D=0$), the warp float ($D=1$) and the weft float ($D=0$) respectively, which agrees the human observation. However, Sample (d) is still detected incorrectly as the weft float ($D=0$). It can be found that the hariness of Sample (d) has a very strong response along the weft direction in Radon transform. Thus, the Local Orientation Pattern (LOP) is developed to describe the fiber orientation frequency in the yarn floats.

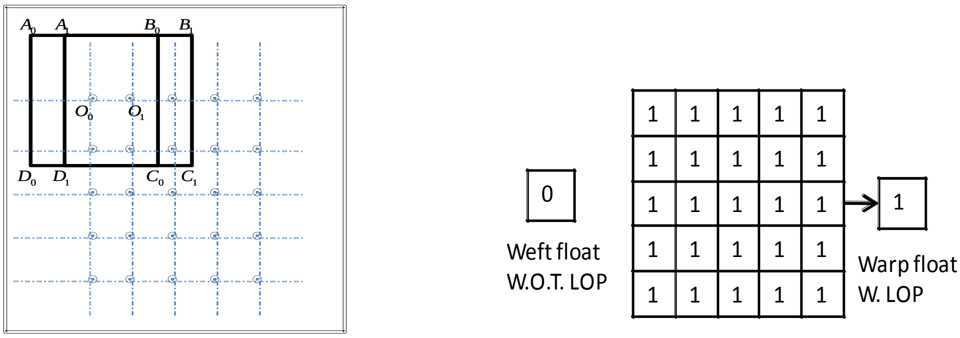
The LOP is defined as a sliding window that traverses the yarn float patch according to the given sampling grid on it. Specifically, the sliding window is a small rectangular window with the size of $Sx \times Sy$, where $\zeta < Sx, Sy < m$. Suppose the size of the yarn float patch is $m \times n$ and satisfies $m \le n$. ζ is a threshold value to define the smallest size of the sliding window. The LOP is given by:

$$LOP = \Psi(\vartheta, \upsilon, S) \tag{35}$$

where ϑ is the orientation angle of the fibers detected from Equation (31), υ is the moving path of the sliding window in the yarn float patch and S defines the window size.

The moving path υ defines the center location of the sliding window when it is traversing on the yarn float patch. As shown in Figure 27, the shadow area on the boundary of the yarn patch should be removed when LOP is calculated. In additional, the moving path can be defined as a grid sampled from the yarn float patch to save the computation cost. In this paper, the moving path is defined by a

5×5 grid in which each node $O(x, y)$ is the location of the center of the sliding window as shown in Figure 31 (a).



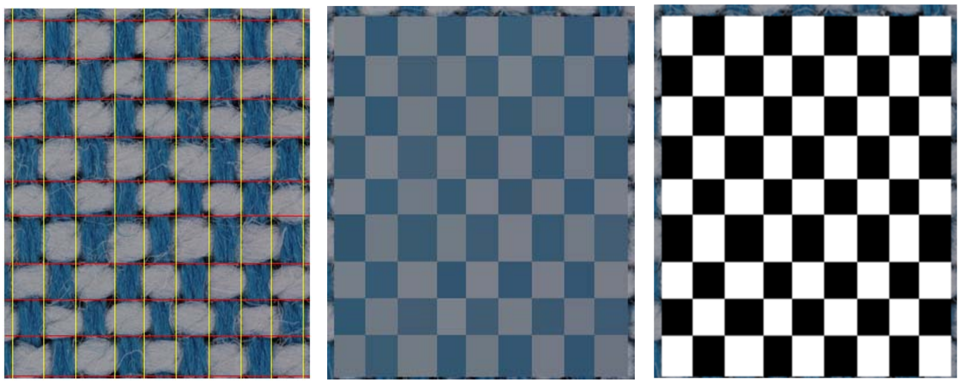
(a) (b)

Figure 31. The moving path of the sliding window (left) and the misclassification correction with LOP detection. (a) the sliding window. (b) local values of the fiber patch.

By using LOP, the misjudgment for Sample (d) in Figure 30 can be corrected and the results are shown in Figure 31 (b), where $D = 0$ means the yarn float is classified as the weft float by using the whole yarn float without LOP detection and $D = 1$ the warp float with LOP. It can be seen that all the fiber orientation responses of the small patches on the yarn float are classified as the warp orientation by LOP. Therefore, Sample (d) is the warp float.

In case that there are different orientation responses in LOP, the voting function described in Equation (34) will be invoked. The proposed detection method also applies to the detection of the fabric structure with the twisted yarns. Figure 32 shows an example of the structure detection result for the twisted yarn fabric by LOP. The details of four twisted yarn patches are shown in Figure 32 (d). It can be found that the proposed method can detect the fabric structure accurately. By calculating the average color of each yarn float patch, the representative color for each yarn float patch can be obtained. The final estimated fabric image combines all the warp and weft floats and the result is shown in

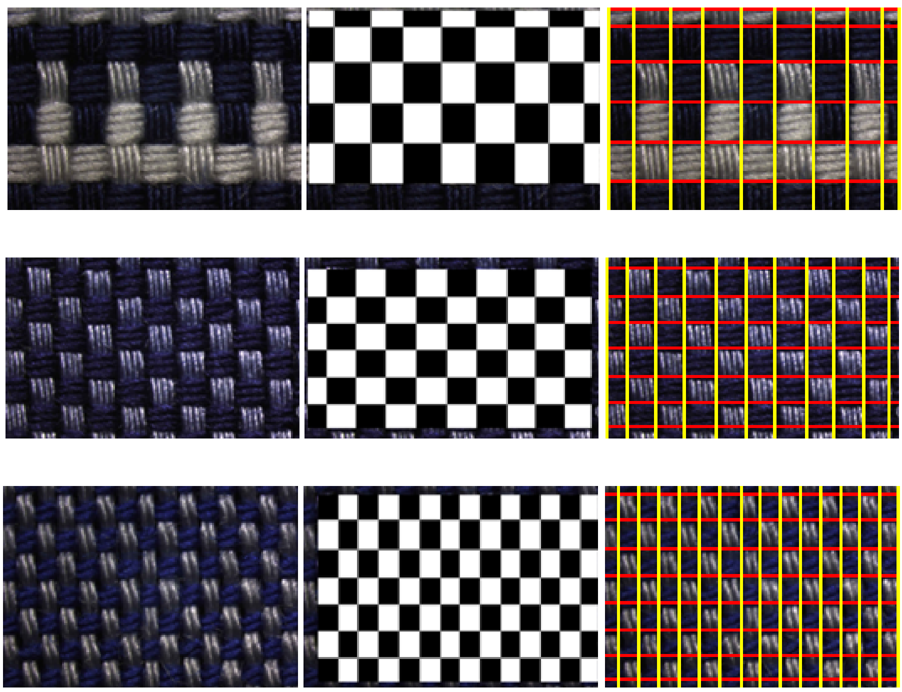
Figure 32 (b). The proposed method can also detect the fabric structure pattern with multiple color effects. Figure 33 shows the experimental results that confirm the effectiveness of the detection method.



(a) (b) (c)

(d)

Figure 32. Fabric structure detection result for the twisted yarns. (a) the fabric with the yarn location grid (the twisted yarn structure). (b) the estimated fabric image. (c) the detection result of the fabric structure. (d) the examples of the twisted yarns from the fabric.



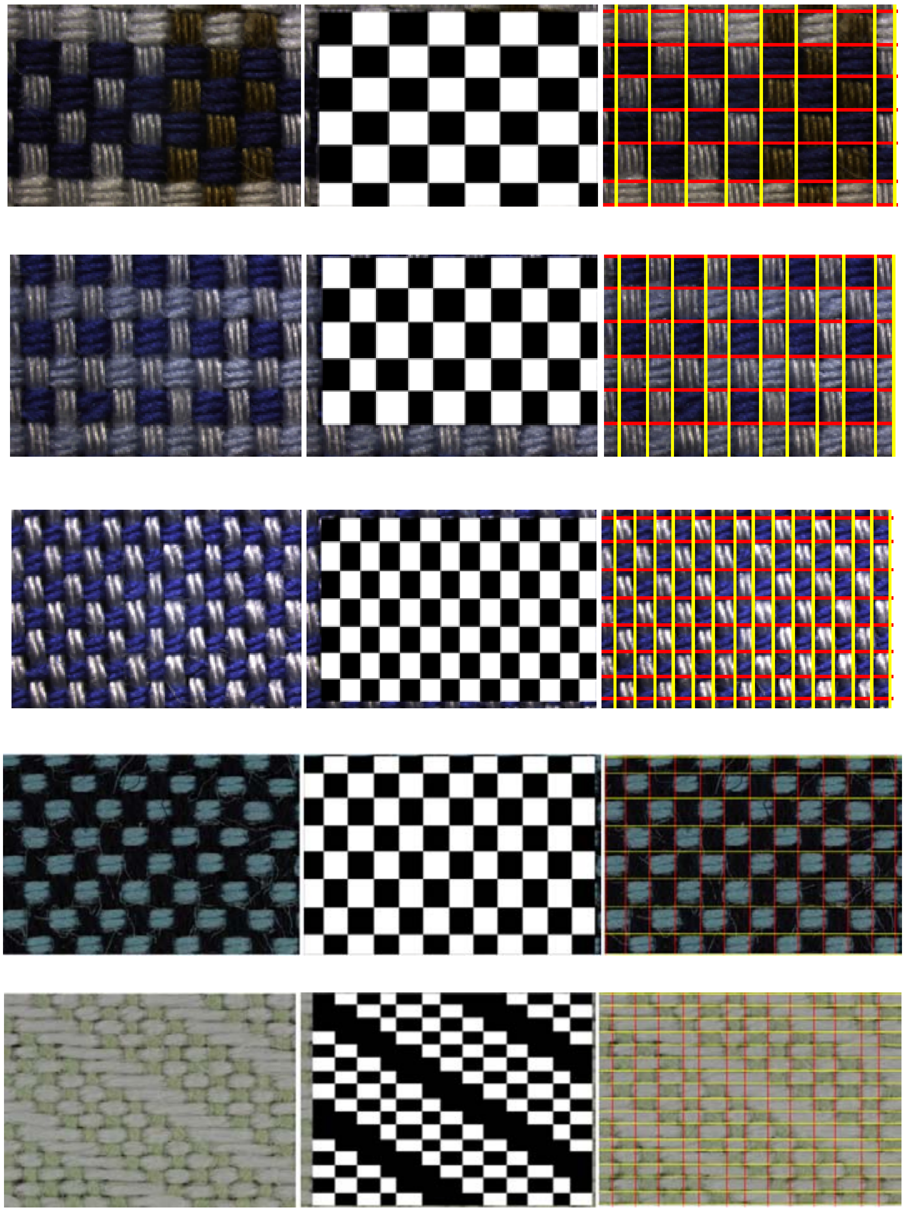


Figure 33. Structure detection results for fabrics with different color effects.

In the experiments, three kinds of fabrics are included in the experiments, i.e. the single yarn fabric, the double yarn fabric and the twisted yarn fabric. The research method has been proven to be effective even with the presence of the hariness on the fabric surface. Importantly, there are two points to be noted. First, the structure detection method is developed for high resolution fabric images. On the other hand, it should be stressed that the whole detection process is supervised, i.e. not fully automatic, for all samples, as the parameter of the peak or valley detection function may need to be adjusted for different samples.

Nevertheless, there are just few parameters to tune for samples with very different structures, typically two parameters (threshold values that are set empirically) for peak detection, one for warp direction and the other for weft. Thus, the developed method is still useful in fabric weave pattern recognition especially when there is prior knowledge about the samples. In the following experiments, the weave pattern recognition results from real fabrics will be used for weave pattern search and evaluation.

4.3 Experiments and discussions

Fabric weave pattern search is considered to be issues of pattern prioritization according to different interests of applications. In this section, I will present the experimental results of the three aspects of weave pattern essential characteristics. The experiments of fabric weave pattern search will be discussed based on different applications.

4.3.1 Weave pattern complexity prioritization

In fabric weave pattern design process, fabric weave patterns are searched by the pattern complexity to optimize production schedule and reduce cost. The first experiment is about prioritization of fabric weave patterns by their pattern complexity. As described in sections 3.1, 3.3 and 4.1.1, the indexing values of weave pattern complexity can be used to rank the weave patterns. In the experiments, 40 users were invited, including designers, sales man, product managers, production technicians, and consumers. There are 20 users who have at least three years design experience. Subjective evaluations of weave pattern prioritization were conducted.

The only way of performing subjective tests of the user is to ask the user to evaluate the prioritization system subjectively. According to the suggestion of users with professional design knowledge, the testing samples were divided into three classes: weave class A, weave class B, and weave class C. The three classes of testing samples are shown in Figure 34. The characteristics of weave class A are: (1) high interlacing frequency of warp and weft yarns, (2) short yarn floats, and (3) indistinct directionality of the pattern. The characteristics of weave class B are: (1) very low interlacing frequency yarns, (2) long yarn floats, and (3) indistinct directionality of the pattern. The characteristics of weave class C include: (1) low interlacing frequency yarns, (2) long yarn floats, and (3) distinct directionality of the pattern.

Weave pattern complexity value is calculated by FFT entropy method and the prioritization result is given in Figure 35. The prioritization is based on the score value of FFT entropy value. Three classes of testing samples and their index number are shown in Figure 34. An evaluation experiment was conducted. A user was asked to give a score for each prioritization of calculations. The lowest score value is 0. The score indicates that the machine prioritization is random. The highest score is 100%. The score shows that the user is fully satisfied with the machine prioritization. The final evaluation score is an average evaluation score from all users. The final score is called the user satisfactory level.

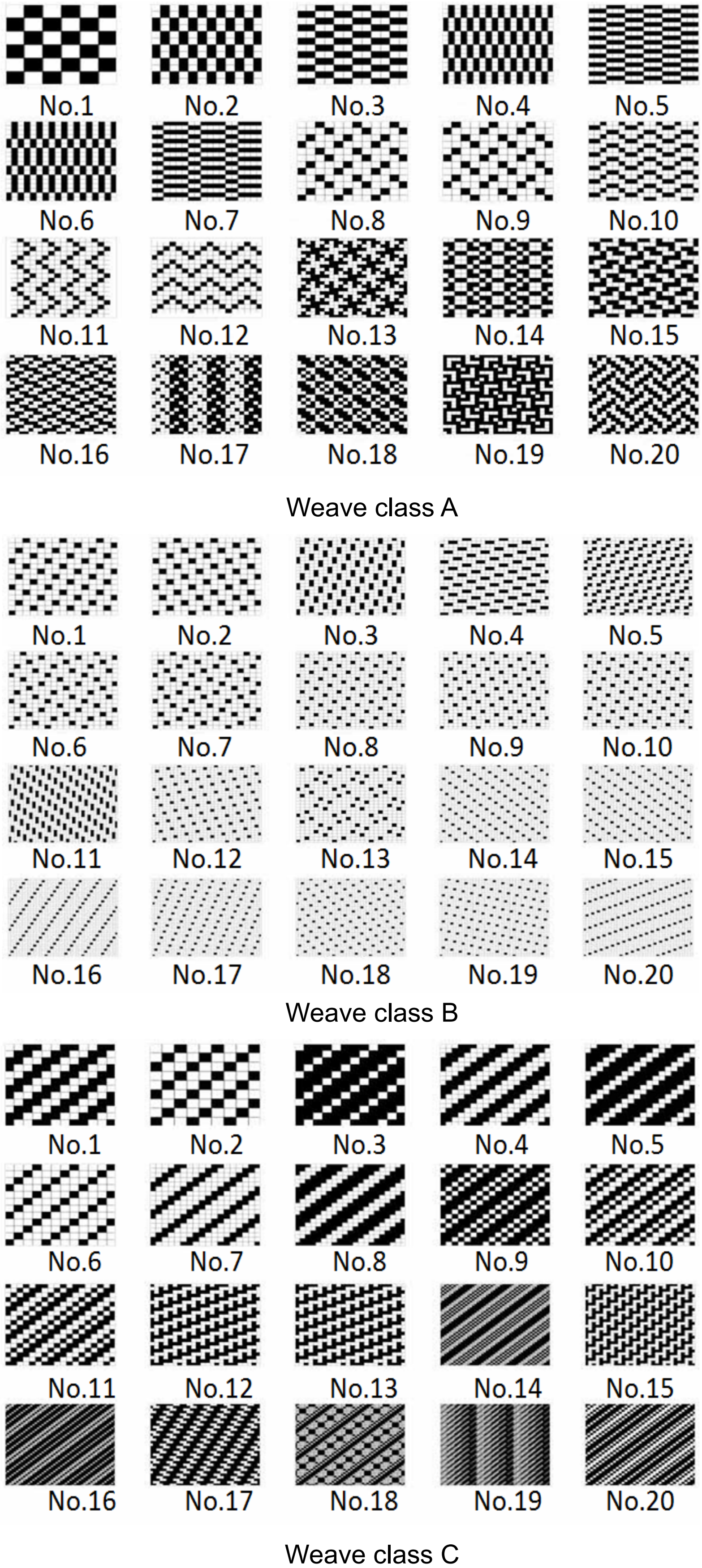


Figure 34. Weave pattern complexity ranking.

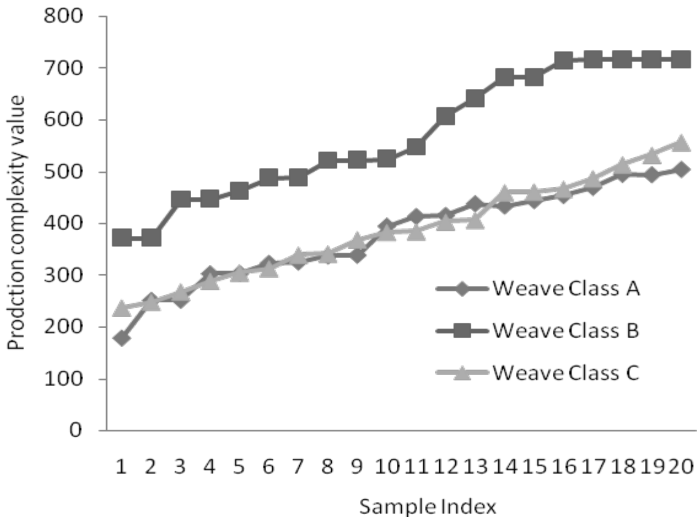


Figure 35. Weave pattern complexity prioritization.

For users with design knowledge, a level of 98% is satisfactory for the average prioritization. For those without design knowledge, only a level of 90% is satisfactory. The total average satisfactory level is 94%. Weave pattern prioritization is highly related to LTM of human brain. Users with fabric design knowledge gave higher scores of satisfactory level based on their understandings of weave pattern production. Users without professional design background tended to give lower scores for the weave pattern prioritization.

The designers also mentioned the reasons for giving higher satisfactory level of the prioritization results. The results reflected several important design aspects in production, including repeat size and woven interlacing complexity. In Figure 35, scores of weave patterns with similar repetition sizes are close. For example, the first row of samples has smaller repetition size than the second row for all classes.

The prioritization results differentiated distance between two weave patterns. Weave patterns with lower FFT entropy scores were ranked at the front. For example, plain weave pattern with repetition size 2 by 2 was ranked at the first position. Plain weave pattern is generally considered as the simplest weave pattern in fabric design. The prioritization results also showed that the complexity differences between classes of A and C were minor in Figure 34. Complexity values of Class B were generally higher than A and C.

4.3.2 Structural appearance prioritization

Fabric is a kind of structured materials. Structural appearance is one of the essential features of fabric textures. The structural appearance of fabrics can be characterized in two ways. The first is the weaving interlaced status of warp and weft yarns. The second is the clustering relation of warp and weft floats. The characteristics of the two aspects are largely determined by the directionality of the yarn float patterns.

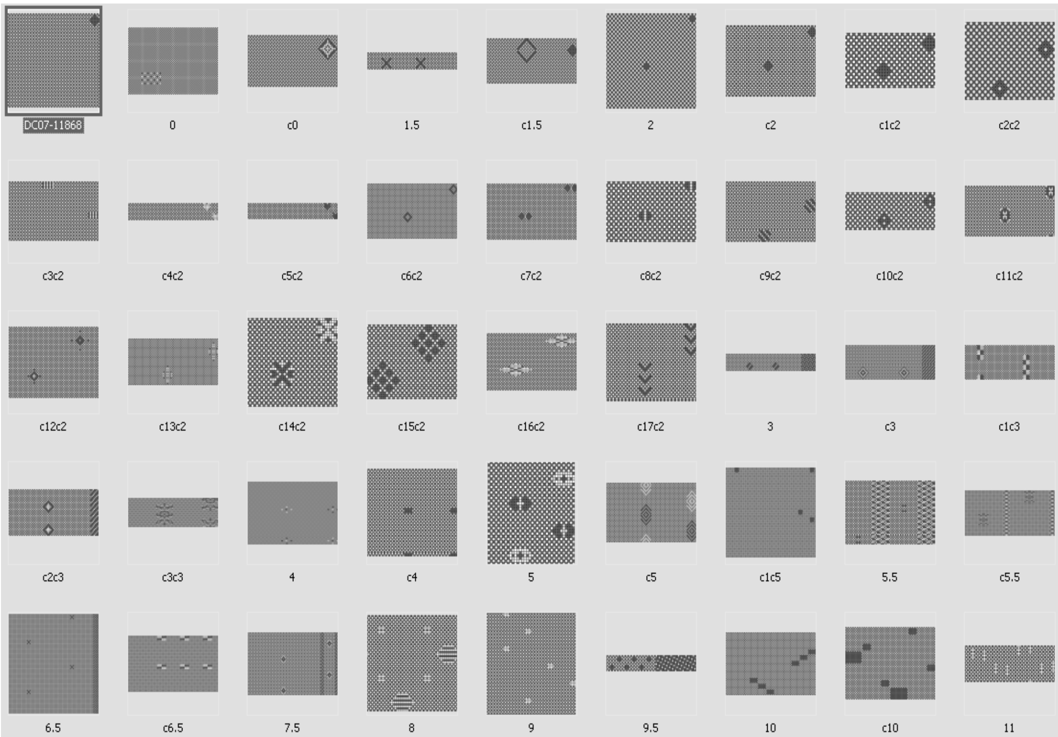
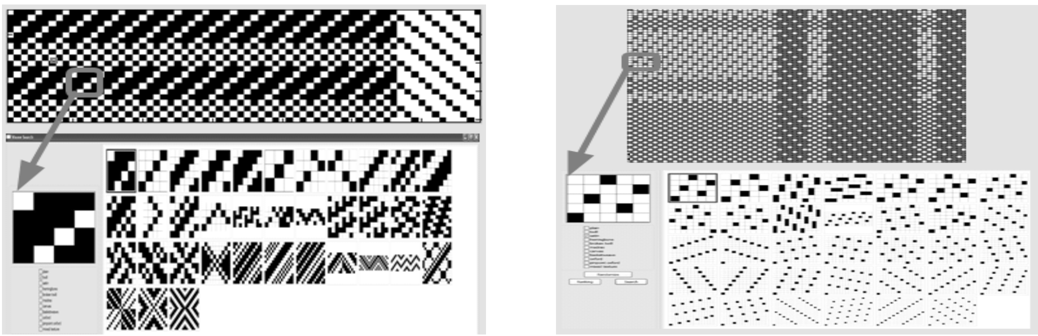


Figure 36. Weave pattern prioritization by DM-Trail-Node.

A fabric weave pattern is considered as a two-phase texture pattern consisting of textons on a regular background. A regular background can be defined as a weave pattern with low values of FFT entropy. Textons are clusters of warp points or weft points. These clusters are characterized by their shape. The LBP (Local Binary Pattern) algorithm is used to detect the locations of textons, since it performs a local search of texture patches without global texture calculation [82].

Based on locations of textons, weave patterns are prioritized by DM-Trail-Node. One typical prioritization result is shown in Figure 36. The first pattern in the first row is the simplest structural pattern in fabric design. There is one texton on a regular background. The prioritization is based on the values of DM-Trail-Node. The first pattern is a reference pattern. It is followed by patterns with close values of DM-Trail-Node. Values of DM-Trail-Node are calculated between the reference pattern and each pattern from the dataset.



a) b)

Figure 37. Texton prioritization. (a) texton twill prioritization. (b) texton satin prioritization.

The weave pattern can also be prioritized according to FFT entropy values of textons and backgrounds. In Figure 37 a) twill texton has been selected as the reference pattern for prioritization of textons. In Figure 37 b), a satin texton has been selected as the reference pattern for prioritization of textons. Experiments on tag ranking of weave pattern are conducted. The task of tag ranking is to rank the weave patterns according to structural appearance similarity by subjective judgment. The Normalized Discounted Cumulative Gain (NDCG) is adopted as the evaluation measure of prioritization performance. NDCG is described as:

$$NDCG_n = Z_n \sum_{i=1}^{n} (2^{r(i)} - 1) / \log(1+i) \tag{36}$$

where $r(i)$ is the relevance score of the i-th tag and Z_n is a normalization constant that is chosen so that the NDCG of optimal ranking is 1.

The performances of weave pattern texton orientation by DM-Trail-Node and texton prioritization of backgrounds are illustrated in Figure 38. The data size of weave pattern is 5000. The number of texton backgrounds is 500. The average NDCG value is higher for the first two depths (1 and 3) for weave pattern texton orientation prioritization and texton prioritization. The lowest average NDCG value is at depth 5 for weave pattern texton orientation prioritization. The lowest average NFCG value is at 10 for texton prioritization. The results show that the performance of weave pattern texton orientation prioritization is higher than texton prioritization.

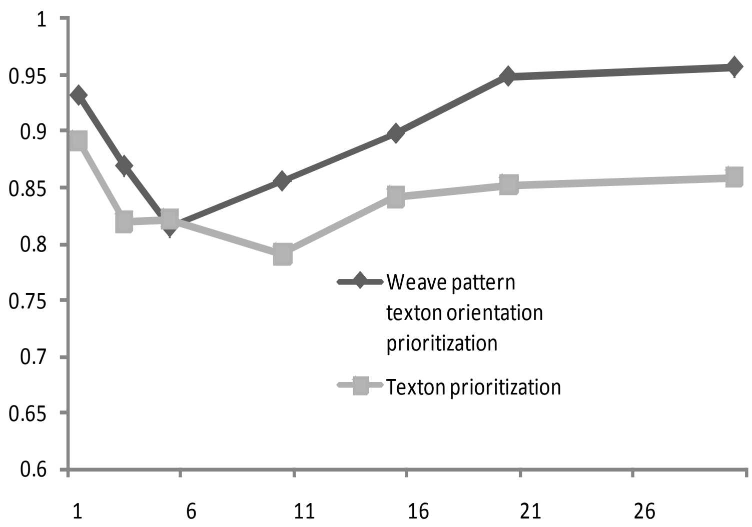


Figure 38. Performances of weave pattern and texton prioritization.

In fabric design, weave pattern structural appearance similarity is conducted in terms of textons orientation and background texton. A weight with value range [0,1] is used to control the prioritization preference between textons orientation and background texton components. When the value of weight is equal to 0, the output is prioritized by textons orientation. When the value of weight is equal to 1, the output is prioritized by background texton. If the weight is equal to (0,1), L_2 distance is used to calculate the prioritization combination of textons orientation and background texton.

4.3.3 Cognitive feature prioritization

Texel repetition and content richness are considered to be the cognitive features to prioritize fabric weave patterns. The texel location and the number of texels are extracted using the approach introduced in Section 4.1.3. These features are used as effective indexing features for weave pattern prioritization. Production parameters can be derived from the texel information. For example, the size of a texel indicates the quantity of material cost for each repetition pattern in a fabric. Weave pattern prioritization by texel size is one of the most important criteria for weave pattern data management in practice.

In Figure 39, there are four weave patterns with different size of repetition. The periodic elements and their locations in the weave pattern are extracted by the method in Section 4.1.3. Each texel is then extracted based on the detected grid marked by lines in dark. The texel of the weave pattern is shown on the right in Figure 39 (the small square pattern). Fabric weave patterns are characterized by the size of texel and the shape of the grid. Thus, there is an underlying grid structure that maps the texel. In this case, the locations of the texels are also determined by the locations of the nodes in the grid. In weave patterns of (a) and (b), there are few repetitions. In weave patterns of (c) and (d), there are more repetitions. Further, for each grid pattern detected from the weave pattern, the regularity of the structural appearance of the nodes can be measured by the method introduced in Section 4.1.2.

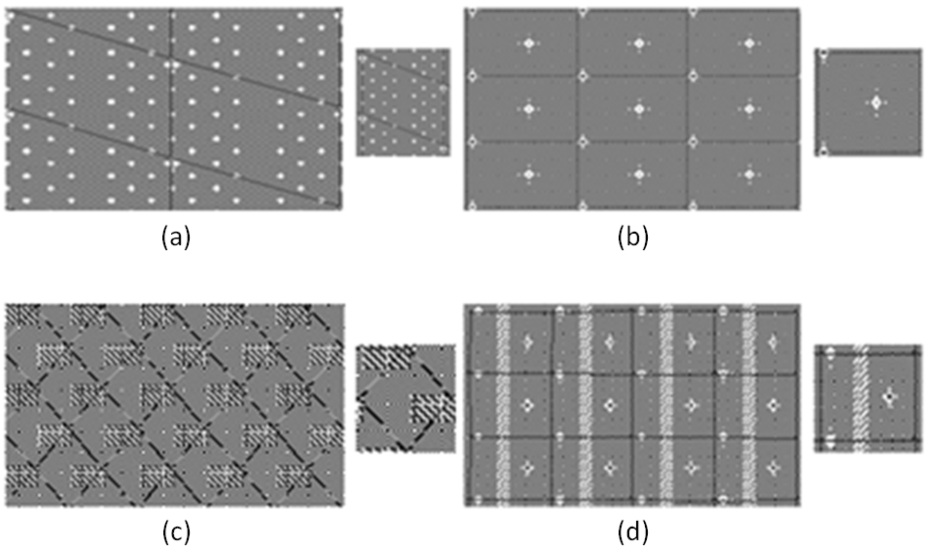


Figure 39. Weave pattern and their texels. (a) Sample (a) and its texel. (b) Sample (b) and its texel. (c) Sample (c) and its texel. (d) Sample (d) and its texel.

Based on the locations of texels, application-oriented prioritization is conducted. As an example, a group of weave patterns in Figure 40 are prioritized according to texel size and the content richness of the texel. Low-level features, including the number of corners and edges are used to describe the content richness of texel.

The prioritization result is given in Figure 40 in which the weave pattern number is the ranked order of calculations. The performance evaluation of the prioritization result is subjective. 40 users were invited for the evaluation, including designer, sales man, product manager, production technician, and consumer.

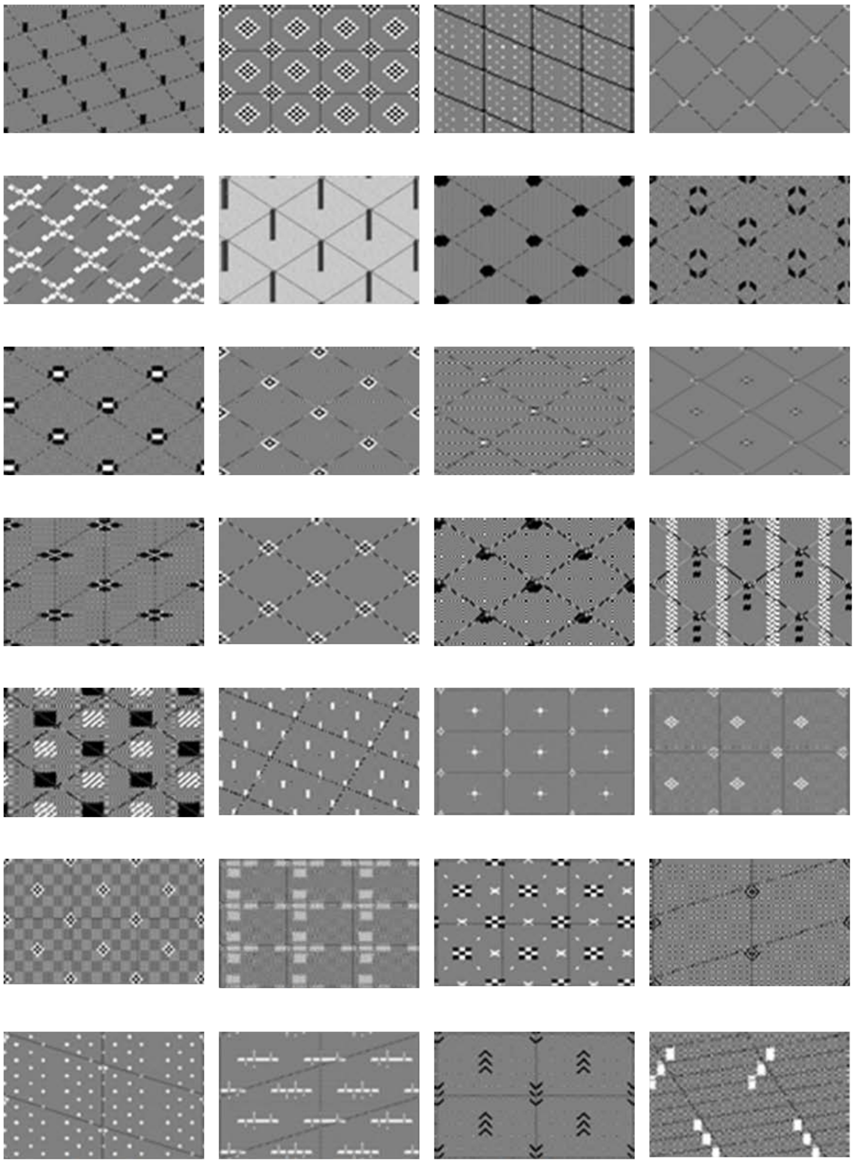


Figure 40. Weave pattern prioritization by features of texel.

In the experiments, the total average satisfactory level for 40 users is 92.6%. The satisfactory level is defined in Section 4.3.1. Users are more interested in global texture features rather than local texture variations. According to the explanation of cognitive informatics, it is true because the function of human beings memory is working as an abstract thinking engine. The abstract thinking engine captures global texture features rather than local texture details, such as shape of patterns in the texel.

4.4 Summary

This chapter develops fabric texture attributes for search. Application-oriented search methods are proposed and discussed. The customized prioritization methods for weave pattern search are based on the OAR model. Three essential attributes and their mathematical calculation methods for weave pattern search are proposed, i.e. weave pattern complexity, structural appearance and cognitive features. A key feature for the representation of attributes is elaborated. The key feature is defined as weave structural representation. In order to capture fabric macro and micro textures, novel fabric image acquisition methods are proposed and the necessities of image acquisition conditions are discussed. Automatic and interactive fabric pattern recognition methods are developed. Fabric pattern recognition produces weave pattern images, which are key fingerprints for fabric texture search. Fabric attributes and features in OAR model are tailored to describe essential characteristics of fabric textures for fabric swatch documentation and searching.

Chapter 5:

Weave Pattern Classification

This chapter provides fabric weave classification techniques based on the guidance of OAR model in Section 3.1 and 3.3. It is organized in four major sections. Section 1 introduces weave pattern classification techniques based on material-based organizational structure of weave patterns, especially in terms of weave pattern directionality and complexity. Section 2 proposes a method of fabric texture classification which provides new perspectives to fabric swatch management and categorization. Section 3 presents experimental results and this chapter is concluded in Section 4.

5.1 Weave pattern taxonomy

Different weave patterns are used to demonstrate texture characteristics in the needs of design. Traditionally, the designer classifies and arranges fabric swatches according to various conventions.

In textile design, weave patterns are classified or categorized according to their interlacing rules by three categories: plain weave effects, twill weave effects and satin weave effects. The taxonomy is illustrated in Figure 41. There are regular patterns and irregular patterns. The former includes the three basic families: (1) plain, (2) twill and (3) satin, as shown in Figure 42 (a), (b) and (c) respectively. The irregular patterns are the patterns that exhibit the characteristics of stochastic textures, for example, crepe weaves as shown in Figure 42 (d) and (e). The interlacing rules determine the appearance across the fabric surface, which is constrained by maximum weaving yarn floats during the manufacturing process. As shown in Figure 41, many types of these patterns, such as the coarse twill and satin distribution reveal the yarn floats arrangements. The characteristics of different categories should be carefully selected and represented to differentiate these interlacing rules. In the following sub-sections, the techniques of classifying weave patterns will be discussed according to the content-based characteristics of weave patterns.

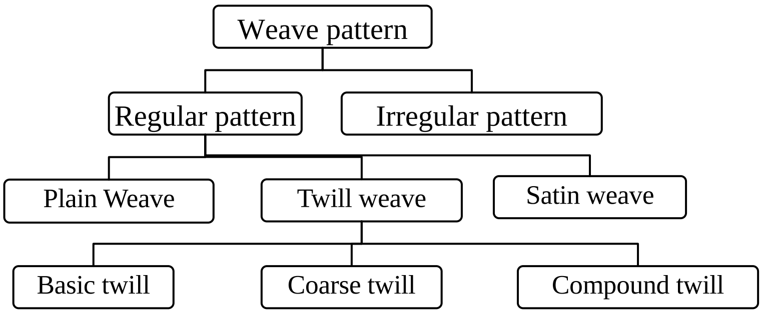


Figure 41. Taxonomy of fabric weave pattern.

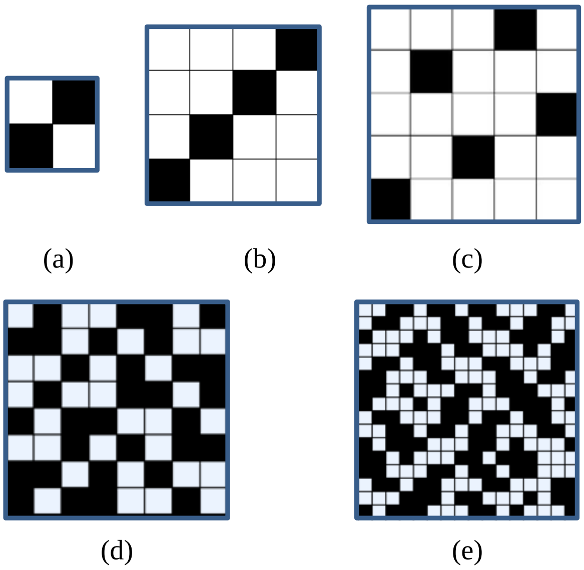


Figure 42. Examples of weave patterns. (a) plain weave pattern. (b) twill weave pattern. (c) satin weave pattern. (d) crepe weave pattern 1. (e) crepe weave pattern 2.

5.1.1 Regular patterns description and classification

To simplify the complexity of categorization methods of fabric weave patterns, it is necessary to use a simple method to represent these simple samples in the regular weave patterns. There are many fabrics of simple and regular rules in weave arrangement as shown in Figure 6. For these weave patterns, the distribution rules of weave points can be directly extracted through simple mathematic description for differentiation or classification.

Matrix Ψ is used to describe a weave pattern as follows:

$$\Psi = \begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{pmatrix} \tag{37}$$

where, $a_{ij} = \{0,1\}; i = 1,2,\ldots,m; j = 1,2,\ldots,n;$ a_{ij} taking the value 0 means weft point and 1 means warp point. Each column denotes the warp interlacing rule in the fabric: $\{a_1,\ldots a_j,\ldots a_n\}$. The interlacing rule for each warp can be described by the following formula:

$$a_j = \frac{c_1 c_2 \ldots c_x \ldots c_p}{d_1 d_2 \ldots d_x \ldots d_p} \tag{38}$$

where c_x means the warp float points and d_y means the weft float points; (p + q)is the number of interlacing times between warp and weft float points.

Based on the definitions above, three types of regular weave patterns can be described: Regular Plain Weave Pattern (RPWP), Regular Twill Weave Pattern (RTWP) and Regular Satin Weave Pattern (RSWP). The value of a_{ij} can be deduced by the index of previous warp point position (subscript position) in the matrix. The step in warp and weft is used to describe the warp point distribution rule, s_j meaning step in warp direction and s_w meaning step in weft direction. For these regular patterns, there is a pre-requisite condition:

$$m = n = \sum_{j=1}^{p} c_j + \sum_{j=1}^{q} d_j \tag{39}$$

For RPWP, the yarn interlacing rule can be expressed as:

$$a_1 = \frac{1}{1}, (c_1 = 1, d_1 = 1, p = q = 1), s_j = s_w = \pm 1 \tag{40}$$

For RTWP, the rules of yarn interlacing can be subdivided into three categories. The first one is basic twill, which can be described as:

$$a_1 = \frac{c_1}{d_1}, (c_1 + d_1 \geq 3, p = q = 1), s_j = s_w = \pm 1 \tag{41}$$

The second one is coarse twill, which can be given by:

$$a_1 = \frac{c_1}{d_1}, (c_1 + d_1 \geq 4, c_1 \neq 1, d_1 \neq 1, p = q = 1),\ s_j = s_w = \pm 1 \tag{42}$$

When $c_1 > d_1$, technician calls it warp effect coarse twill; when $c_1 < d_1$, technician refers to as weft effect coarse twill; $c_1 = d_1$ is the double face coarse twill. The third type is compound twill, that is:

$$a_1 = \sum (c_1 + c_2 + \ldots + c_p + d_1 + d_2 \ldots + d_q) \geq 5,$$

$$m = n \geq 2, s_j = s_w = \pm 1 \tag{43}$$

For RSWP, warp effect is:

$$a_j = \frac{c_1}{1}, c_1 \geq 4(c_1 \neq 5), p = q = 1, \tag{44}$$

where $1 < s_j < c_j$, $(c_j + 1)$ and s_j are relatively prime.

Weft effect is described as:

$$a_j = \frac{1}{d_j - 1}, d_1 \geq 5(c_1 \neq 6), p = q = 1, \tag{45}$$

where, $1 < s_w < (d_j - 1)$, d_j and s_w are relatively prime.

5.1.2 Irregular patterns description and classification

It is relatively easy to define and differentiate the regular patterns by their simple arrangements of yarn interlacing points and step. However, for many fabric weave patterns, their step in warp or weft is not a fixed number. In this case, smoothness and connectivity is adopted to describe and classify these irregular patterns.

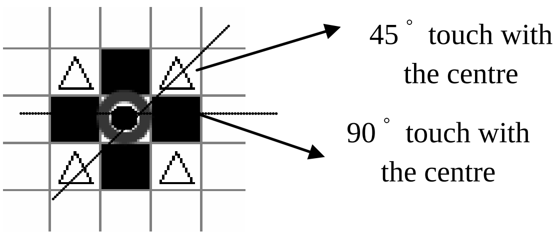


Figure 43. 45° and 90° connection.

To describe weave pattern distribution, the relative position of the warp points and weft points is investigated. Smoothness and connectivity can be used to capture their distribution in the diagram. The smoothness is measured by the horizontal, vertical and diagonal transitions, and the connectivity is measured by the number of black (warp / black point with nominal value equals 1) and white (weft / white point with nominal value is 0) clusters.

Before doing the calculations of smoothness and connectivity, satin weave is differentiated from plain and twill weaves. As shown in Figure 3, the centre interlacing point of interest has two kinds of connections with its neighbors: toughing each other by 45° (i.e., $(i+1, j\pm1)$ or $(i-1, j\pm1)$) or by 90° (i.e., $(i, j\pm1)$ or $(i\pm1, j)$). 90° touching is known as four-connectivity, and 90° / 45° touching is known as eight-connectivity. In the satin weaves, they may or may not have 90° touch with the centre. But for 45° touch with the centre, it is not common to have this kind of connection. For the reasons of simplicity, it is taken as a criterion to discriminate satins weaves from plain and twill weaves. (If there are exceptions, the user can adopt an enforcement rule to take this situation into consideration.)

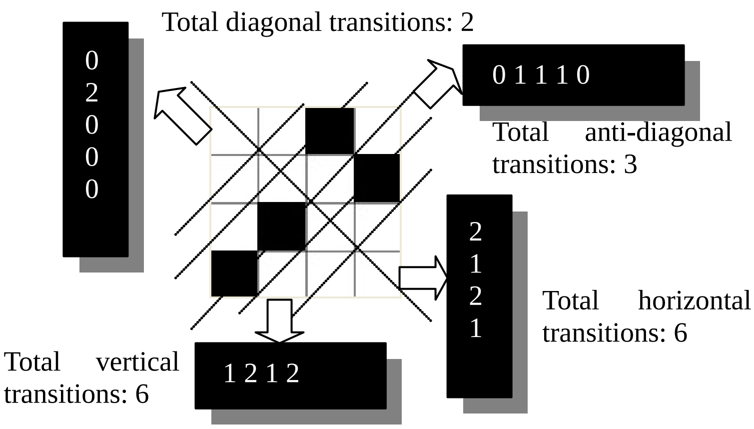


Figure 44. Illustrations of transitions calculation.

The smoothness of the interest neighborhood around pixel $\tau_{i,j}$ is measured by the total number of horizontal, vertical, diagonal and anti-diagonal transitions: E_1 (horizontal), E_2 (vertical), E_3 (diagonal), E_4 (anti-diagonal). $\tau_{i,j}$ is the value of the i^{th} weft and j^{th} warp in the weave pattern. In order to describe the distributions of the four directions transitions, the variance of the four-direction transitions array $\left\{E_1, E_2, E_3, E_4\right\}$ is shown as:

$$v'^2 = \frac{1}{n}\sum_{i=1}^{n}(E_\varphi - E_i)^2, \tag{46}$$

$$E_1(i,j) = \sum_{\mu=-1}^{1}\sum_{\nu=-1}^{1}\xi(\left\{\tau_{i+\mu,j+\nu} \neq \tau_{i+\mu,j+\nu}\right\}), \tag{47}$$

$$E_2(i,j) = \sum_{\mu=-1}^{1}\sum_{\nu=-1}^{1}\xi(\left\{\tau_{i+\mu,j+\nu} \neq \tau_{i+\mu,j+\nu}\right\}), \tag{48}$$

$$E_3(i,j) = \sum_{\mu=-1}^{0}\sum_{\nu=-1}^{0}\xi(\left\{\tau_{i+\mu,j+\nu} \neq \tau_{i+\mu+1,j+\nu+1}\right\}), \tag{49}$$

$$E_4(i,j) = \sum_{\mu=0}^{1}\sum_{\nu=-1}^{0}\xi(\left\{\tau_{i+\mu,j+\nu} \neq \tau_{i+\mu-1,j+\nu+1}\right\}), \tag{50}$$

where $\xi(\cdot)$ is an indicator function taking value from $\left\{0,1\right\}$. An example of broken twill weave is given in Figure 44 to illustrate the calculation of transitions in four directions. Given a reference value $v'^2 = \varpi$ as plain weave category for differentiation of plain weave and twill weave, if $v'^2 \in (\varpi - \delta, \varpi + \delta)$, the pattern can be classified into plain weave category (Otherwise, it is twill weave pattern). Here increment $\left|\pm\delta\right|$ is threshold value for the judgment.

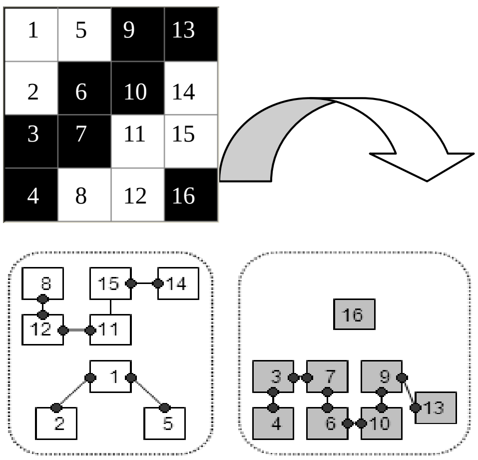
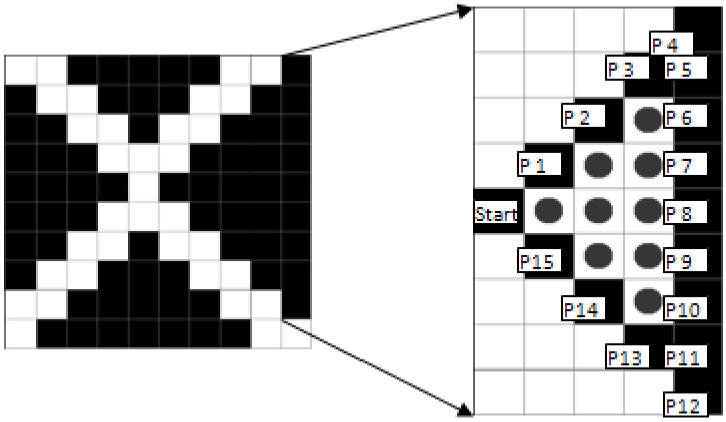


Figure 45. Illustration of connectivity calculation (top: a regular twill pattern and bottom: connected clusters).

After the calculation of smoothness, connectivity is used to differentiate plain weave and twill weave. As illustrated in Figure 43 and Figure 45, the connectivity is measured by the number of the black and white clusters. In order to make a differentiation between plain weave and twill weave, the 90° connection criterion shown in Figure 43 is used to describe the connectivity. Figure 45 is an example of 4×4 pattern with eight white points forming two clusters and with eight black points forming two clusters. The number of clusters can be automatically identified by traversing the graph using depth-first search strategy [108, 109]. A stack-based search algorithm can be used to calculate the connectivity of 90 degree.

Suppose that there are Γ interlacing points in total and the final value of ε indicates the number of clusters. Let $v(k)$ store the value of k^{th} interlacing point and v_0 be the interlacing value of interest. Set up an empty stack and an P-element array $L[\cdot]$ for storing the index of the cluster that the interlacing point belongs to; set $L[k]=0$ for all $k=1,2,\ldots,P$; $i=1$; $\varepsilon=0$. Step Ⅰ: if $L[i]\neq 0$ or $v[i]\neq v_0$, go to final step (Step Ⅴ). Step Ⅱ, $\varepsilon=\varepsilon+1$; push node-$i$ into the stack. Step Ⅲ, if the stack is empty, go to Step Ⅴ. Step Ⅳ, $L[k]=\varepsilon$. Find all pixels connected with k. For each connected interlacing point j, if $L[j]=0$ (i.e. it has not been visited or pushed into stack), let $L[j]=-1$, push node-j into stack (by the definition of connected, $v[j]=v_0$). Go back to Ⅲ. Step Ⅴ, $i=i+1$; if $i>\Gamma$, stop, otherwise go to Step Ⅰ. The number of clusters is used as supplementation of judgment criterion between plain pattern and twill pattern.



(a) (b)

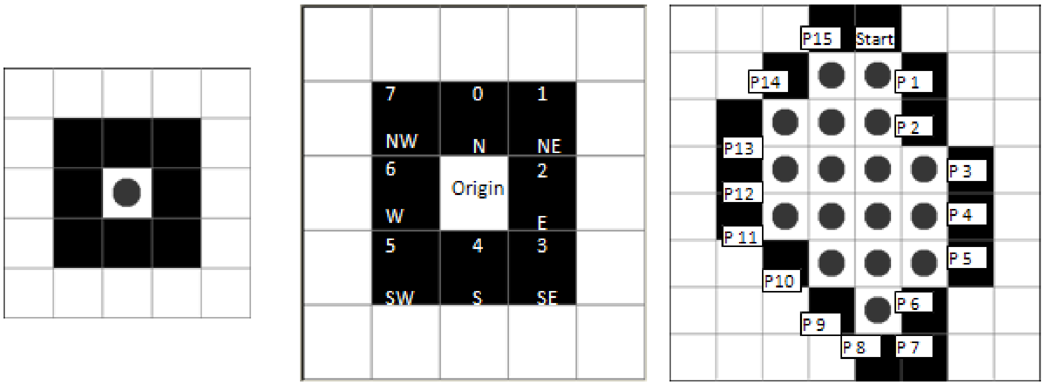
Figure 46. Region and contour description of a twill pattern. (a) a compound twill region. (b) the encoded boundary.

In twill weave pattern, the black cluster may contain a region that need to compare and recognize in an efficient way. Thus, for purpose of recognition the properties of groups of black points are described. A region of the black cluster describes interior points (or contents) surrounded by a boundary (or perimeter). An example of twill pattern and its region description is shown in

Figure 46.

To investigate the properties of a region, its contour can be measured, which is also referred to measurement of the shape.

A point can be defined to be on the boundary if it is part of the region and there is at least one point (white point) in its neighborhood that is not part of the region. The boundary itself can be found by the following: first find one point on the contour and then progress round the contour either clockwise or anticlockwise to search the nearest contour point. To define the interior points in a region and the points in the boundary, neighboring relationship between the points were investigated.



(a) (b) (c)

Figure 47. Contour description code. (a) eight-way neighbors. (b) eight-way code description. (c) sample region and contour code.

The complete neighboring points in eight-way is used to describe the point's relationship. All the eight points surrounding a chosen point are analyzed for this relationship illustrated in Figure 47 (a). In this figure, the point is shown as a circle point in the centre and its neighbors as square. The eight extra neighbors in eight-way relationship are those in the directions North (N), East (E), and South (S), West (W), and 45 degree between them, i.e. North-East (NE), South East (SE), South West (SW), and North West (NW).

The coordinates of a sequence of points can be stored to obtain a representation of a contour. The relative position between consecutive points is then stored. This is called chain code and is formed by concatenating the number that designates the direction of the next point. Given a point, the successive direction from one point to the next point becomes an element in the final code. This is repeated for each point until the start point is reached when the contour is completely analyzed. Directions in eight-way relationship can be assigned as shown in Figure 47 (b). The code for the example region is shown in Figure 47 (c).

The direction from the start point to the next is South East (i.e. code 3) in

Figure 47 (c), so the first element of the contour code describing the region is 3. The direction from P1 to the next, P2, is South (code 4), so the next element of the code is 4. The next point after P2 is P3, which is South East. This coding is repeated until P15, which is connected eastwards to the starting point. To have start point invariance, the digits can shifted cyclically, i.e. replacing the least significant digit with the most significant one, and shifting all other digits left one place. The smallest integer is returned as the start point invariant contour description code. For example, in the Figure 47(c), the initial code (beginning from the star point S) is:

$$code1 = \{3,4,3,4,4,5,4,6,7,7,7,0,0,1,1,2\},$$
$$start = S \tag{51}$$

The result of the first shift is shown as:

$$code = \{4,3,4,4,5,4,6,7,7,7,0,0,1,1,2,3\}$$
$$start = P1 \tag{52}$$

The result of one shift is equivalent to the code that would have been derived by using point P1 as the starting point. The result of two shifts is the description code equivalent to starting at point P2:

$$code = \{3,4,4,5,4,6,7,7,7,0,0,1,2,3,4\}$$
$$start = P2 \tag{53}$$

To obtain a code that is corresponding to the minimum integer, there is at least another shift. The minimum integer code is the minimum of all the possible shifts and is the description code that would have been derived by starting at point P11, which is given by:

$$code = \{0, 0, 1, 1, 2, 3, 4, 3, 4, 4, 5, 4, 6, 7, 7, 7\}$$

$$start = P11 \tag{54}$$

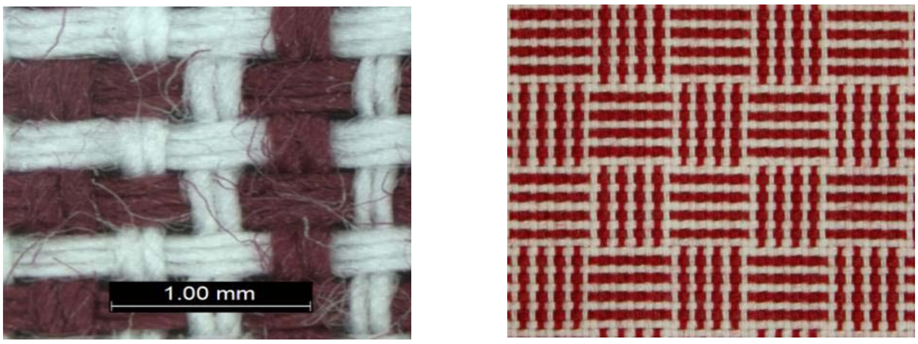
The contour code could be used to describe the regions inside the compound twill. For each region in the compound twill, it is relatively easier to shift to achieve a minimum integer and compare the regions. Finally, combining connectivity, cluster and smoothness descriptors, patterns which belong to twill or plain effects can be differentiated.

5.2 Fabric texture classification

As one of the most common man-made textures in real life, there are many classification criteria for fabric textures. This section comprises two parts. In the first part, the characteristics of fabric textures are studied based on the fabric images captured by different equipment. Then, in the second part, structure-based statistical features are proposed to classify fabric textures.

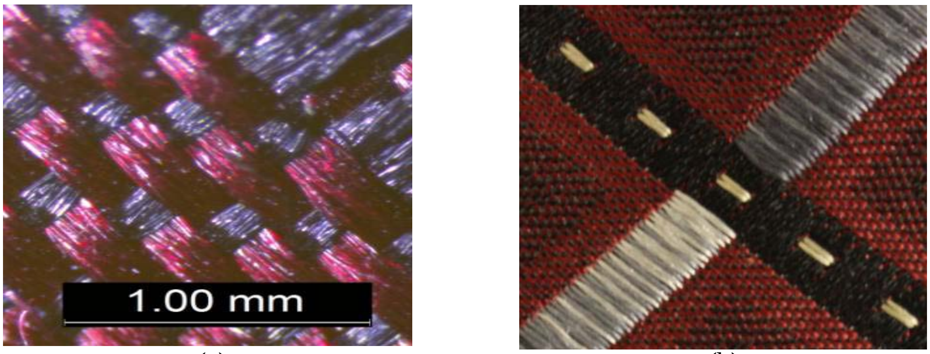
5.2.1 Material-based content

In order to address the essence of surface appearance of fabric material, images of fabrics are captured and compared. Leica M165C has been used to capture the surface appearance of fabrics. In particular, the two kinds of materials, cotton and silk, have been used in the experiments. The image acquisition consists of illuminating a fabric swatch with a point source light and photographing it through a macro lens at a fixed magnification that enables the yarns and fibers to be discerned. The results are shown in Figure 48 (a) and Figure 49 (a). The yarn structures as well as the fiber details of the fabrics are quite different for different materials.



(a) (b)

Figure 48. Cotton fabric images captured by different equipment. (a) Leica M165C. (b) Canon EOS 450D.



(a) (b)

Figure 49. Silk fabric images captured by different equipment. (a) Leica M165C. (b) Canon EOS 450D.

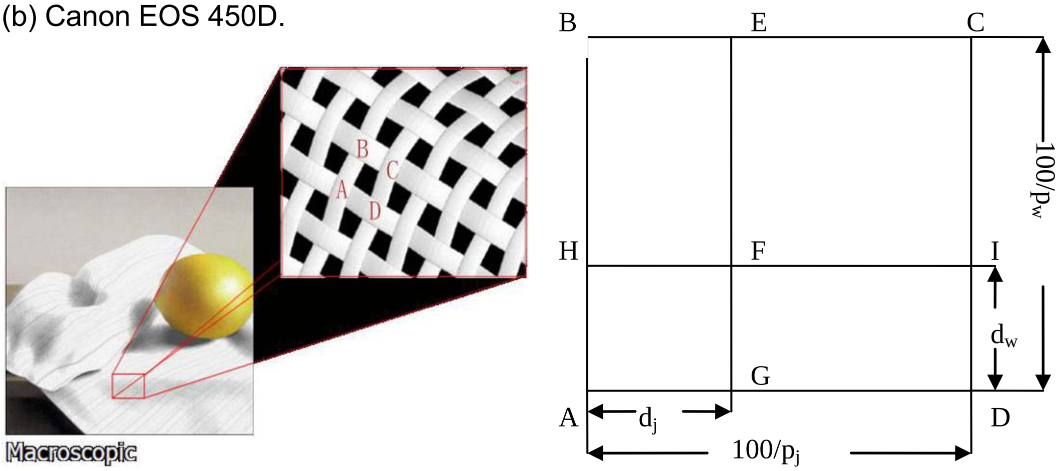


Figure 50. Fabric cover. (a) the aperture between yarns. (b) fabric cover illustration.

On the other hand, the fabric images are obtained by using Canon camera (EOS 450D) for each fabric material. The image is shown in Figure 48 (b) and Figure 49 (b) (the shutter speed is 1/64 sec; the lens aperture is F/5.7; the focal length is 50mm; Exposure time is 1/60 sec; the ISO speed is 400; the F-number is F/5.6). Note that the colors of the images obtained from different equipment are not comparable. Since the focus of this study is texture, the color difference of the samples is not taken into account. From the captured result, the fiber details could not be perceived at the macro-scale level of the fabric surface. Furthermore, the contents of the samples are different because the sampled areas are different, for instance, the texture pattern of Sample (a) in Figure 48 is different from that of Sample (b) in Figure 49. This makes the texture classification difficult at yarn level for large patterns of fabrics. For silk fabric, besides, there is special light reflection. Especially, the light reflection is distinct at the micro level, as shown in Figure 50 (a). Hence, even for the same fabric sample, the fabric texture appearance observed is at least depended on several factors, such as imaging level (micro or macro) and material types. So, in fabric image feature extraction, these factors make the classification of fabric images difficult.

One of the factors that play an important role in determining the texture appearances of fabric images is the aperture between yarns. In Figure 48 (a), the aperture between the yarns can be observed. In some fabric product, there may be large aperture between yarns (the fabric has very low density or very fine yarns), for example Figure 18 (a) in Chapter 4. However, in some fabric product, like silk tie, the interstice between the yarns is small, as shown in Figure 49 (a) and (b). In fact, fabric cover in textile design community can be used to evaluate the interstice between yarns in a fabric. As shown in Figure 50 (a) and (b), the fabric cover is given by:

$$E_j = \frac{S_{ABEG}}{S_{ABCD}} \tag{55}$$

where Ej is warp cover. SABEG and SABCD is the area of ABEG and ABCD respectively. Ej is determined by yarn density and its width, i.e. $E_j = p_j d_j$, where Pj is the warp density (ends/10cm) and dj is the width of warp. Alternatively, the yarn count can be used to describe the relationship between Ej and Pj:

$$E_j = kp_j \sqrt{T_{tj}} \tag{56}$$

where k is a constant and Ttj is warp count (tex). Next, weft cover (Ew) can be defined in the same way. The total cover of a fabric is then given by:

$$E = E_j + E_w - E_j E_w \tag{57}$$

where E is the total cover of the fabric.

It is noted that Equation (55) may not be always correct as the yarn configuration and its width are subjected to deformation due to density limitation and yarn count variation. Thus, the fabric cover may not be suitable for describing the interstice between yarns of different types of fabrics. Besides, the fabric cover is also difficult to calculate for the purpose of classifying fabric texture appearances as there are many parameters of fabrics that need to input and then calculate the total cover values in Equation (57).

Next, the combination effects of aperture of yarns and the size of yarns in the fabrics are investigated. In the experiment, colors of the yarns and the layout of the yarns of the fabrics are the same. As shown in Figure 51 (a), densities of the fabric on the left are 73 ends / cm in warp and 35 picks / cm in weft; in

Figure 51 (b), densities of the fabric are 50 ends / cm in warp and 35 picks / cm in weft. There are two categories of warp yarn counts in the two sample, i.e. area A (warp: 80 ends in 8.438 tex) and area B (warp: 80 ends in 9.842 tex). In weft, area C includes 35 picks in 8.438 tex and area D has 35 picks in 9.842 tex.

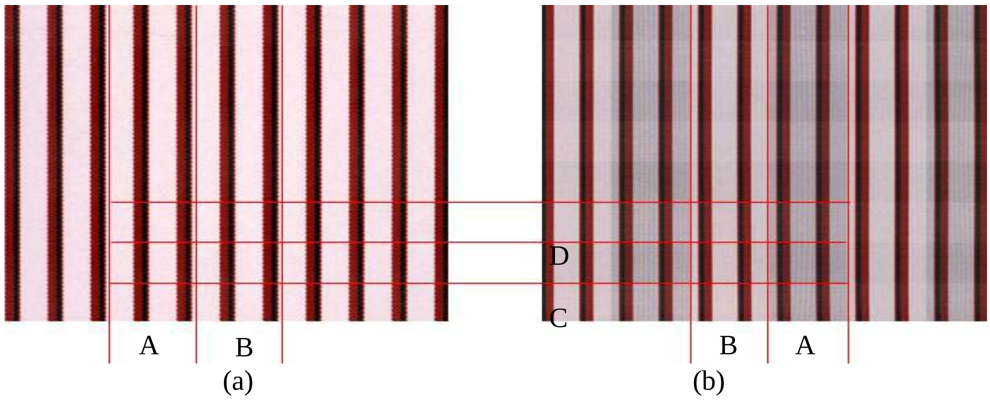


Figure 51. Fabric texture appearances at the macro scale. (a) texture difference of areas cannot be perceived. (b) texture difference of areas can be perceived.

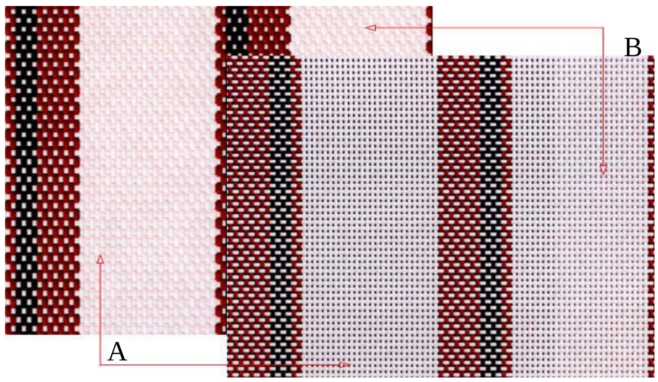


Figure 52. Appearances at meso scale.

In Figure 51, areas of sample (a) could not be differentiated in A and B in warp and C and D in weft. However, the areas of the different structural compositions could be found in sample (b). Considering that this difference is mainly caused by different density and yarn size settings, it can be concluded that there should be a threshold value that is determined by the combined effects of density and yarn size to differentiate the appearances. Intuitively, in fabric image classification, the threshold for differentiating the texture difference of the areas in the fabric samples can be a statistical measurement that can describe the different areas or objects (clusters of points), especially a local texture descriptor. In this case, the traditional global texture features, such as Tamura and Gabor features [97, 110] are not suitable for classifying the fabric textures.

Finally, the fabric texture appearance is investigated at the meso scale (medium scale). In Figure 52, fabric images are obtained by using 5 times magnification of the fabric images in Figure 51. The results show that the fabric texture appearance is depended on the background and the aperture of yarns when the fabric density is low and the yarn size is relatively small. In this case, the background of the sample platform in the image acquisition setting (see Section 4.2.1) should include a set of templates with different bright intensities (for example, black and white background) [111]. The purpose of this is to capture the texture appearance correctly and clearly. For example, a black background is usually needed for a white sample during the image capturing process.

As a summary of the experiments, fabric density, yarn count, background and other factors may significantly affect the texture appearances at different scales of magnification for the fabric images. Further, different weave patterns can have a direct influence on the texture appearance of the fabric as well as these parameters, such as the interstice between yarns and fabric densities [112]. Thus, the statistical geometrical features [113] are preferred to be used to describe a fabric texture in which there is no single factor to solely determine the final texture appearance.

5.2.2 Structure-based statistical features

Texture contents of fabric images vary with material physical resolution in the image acquisition process as shown in the previous section. Two common problems can occur in sensitivity-and-specificity estimates of classes of fabric textures. First, unless a broad spectrum of fabrics is chosen both with and without the condition of color and structure, the study may yield falsely high sensitivity-and-specificity estimates and categorizations, a problem known as spectrum bias. Second, unless the interpretation of the structure design and essence of pattern design could be represented, bias can falsely elevate the test's categorization accuracy, known as workup bias.

Two statistical methods to correct biased problems are developed after the investigations in this study: binary global statistical feature and texel inference feature.

It is more natural to use statistical method to characterize fabric textures due to the complexity of the real materials motivated by the latest findings of Manik and Andrew [114]. They demonstrated that materials can be classified using joint distribution of intensity values over extremely compact neighborhoods and that this can outperform classification using filter banks with large support. The performance of filter banks is inferior to that of image patches with equivalent neighborhoods and the results show that the statistical information of local region is more powerful for material characterization.

Several different techniques to recognition of the general color textures are introduced in the literature [115, 116]. In this study, new texture-based features are developed to characterize fabric images based on the investigation of characteristics of fabric patterns and the statistical geometrical features [113, 116]. In this section, texture features are calculated in the gray image domain. The color of woven fabric is thus not considered. In practice, the method can be used for the classification of the solid-color fabric patterns or the patterns with the same color effects. The role of the color will be described in Chapter 6 from the design point of view. The reason is that weave pattern and its texture appurtenance are of the micro pattern level in textile design and color is usually not the focus especially from the point of view of textile engineering. At the macro pattern level, i.e. the figured-pattern level, color plays an important role in determining the global texture appearance of a fabric pattern, especially from the point of view of aesthetic design.

In this study, the grey channel features have been used to evaluate the contents of images and then classify them. In [113], 16 statistical measures based on the geometrical properties of connected regions in a series of binary images have been proposed to classify images. The binary images called image stack were produced by threshold operations on the grey level image. Geometrical properties like the number of 4-connected regions and their shape description called irregularity together with their statistics (mean, standard deviation) describing the stack of binary images are introduced.

There are two options to produce the image stack: even and non-even threshold separating. A desired set of binarization levels can be used which is parameterized by an initial threshold α_0 and a step $\Delta\alpha$. The series of threshold values is given by $\alpha_i = \alpha_0 + \Delta\alpha$, with $i = 0,...,S_{Bins} - 1$, where S_{Bins} is the number of image layer in the image stack. For an image $I(x, y)$ with G grey levels, a binary image $I_{B\alpha}(x, y)$ can be obtained by thresholding with a threshold value $\alpha \in [1, G-1]$ which results in:

$$I_{B\alpha}(x,y) = 1, \text{ for } I(x,y) \geq \alpha$$

$$I_{B\alpha}(x,y) = 0, \text{ for } I(x,y) < \alpha \tag{58}$$

The first group of '1' valued pixels is defined as being a 4-connected region if for all pixels in the group, each pixel has at least one 4-connected neighbor within the group. The second groups of '0'-valued pixels are similarly defined. Let the number of connected regions of l-valued pixels in the binary image $I_{B\alpha}(x,y)$ be denoted by $NC_1(\alpha)$ and that of 0-valued pixels in the same binary image by $NC_0(\alpha)$. Both of $NC_1(\alpha)$ and $NC_0(\alpha)$ are functions of $\alpha, \alpha \in \{1,...,G-1\}$. Two sets of geometric properties are used by [113]. The first is a simple count of the number of connected regions. The second is to use average measure of region characteristics weighted by region size. The statistical meaning is defined as:

$$IRGL_k(\alpha) = \frac{\sum_{j=1}^{NC_k(\alpha)} IRGL_j(\alpha) \cdot NOP_j(\alpha)}{\sum_{j=1}^{NC_k(\alpha)} NOP_j(\alpha)} \tag{59}$$

where, $k=0$ for '0'-valued regions and $k=1$ for '1'-valued regions, j is the jth 4-connected region, $NOP_j(\alpha)$ is the number of pixels in the jth region at grey level α. In [113], to each of the connected regions (of either '0'-valued pixels or '1'-valued pixels), a measure of irregularity (un-compactness) is applied, which was defined to be:

$$IRGL = \frac{1+\sqrt{\pi} \cdot \max_{i \in I} \sqrt{(x_i - \overline{x})^2 + (y_i - \overline{y})^2}}{\sqrt{|I|}} - 1 \tag{60}$$

where I is the set of all indices to pixels in the region, $|I|$ is the number of indices (the cardinality of the set I), and $(\bar{x}, \bar{y})$ can be thought of as the center of mass of the connected region under the assumption that all the pixels in the region are of equal weight, which is equal to:

$$\bar{x} = \frac{\sum_{i \in I} x_i}{|I|}, \bar{y} = \frac{\sum_{i \in I} y_i}{|I|} \tag{61}$$

In Equation (60), the compactness or the opposite description un-compactness is used to evaluate the irregularity of the region of interest. It is noted that only the maximum value of the cardinal distance from the center of mass of the 4-connected pixels is used to estimate the spatial distributions of pixels. Thus, it may not be suitable for describing fabric textures with fuzzy appearances. This is because the fiber distribution, their profile, and length are difficult to define, i.e. it is more suitable to consider it as random texture in this point. However, there may be no such kind of fiber protruding on the fabric surface. The structure-based texture description should have the ability to capture the main region of the fabric appearance which is also presented through brightness intensity at this point. A new region compactness measure is given by:

$$RCGL = \frac{1 + \frac{\sqrt{\pi}}{n} \cdot \sum \sqrt{(x_i - \bar{x})^2 + (y_i - \bar{y})^2}}{\sqrt{|I|}} \tag{62}$$

where $(\bar{x}, \bar{y})$ is the average value of coordinates of the boundary pixels, n is the number of boundary pixels in the region of interest.

Given a connected region A in 2-D plane, the extent of its regularity or compactness (in sense that the disk has the most compact shape) can be measured by the sum of its radius to the square root of the area, where the sum radius is defined to be:

$$R_{sum} = \sum \sup_{(x,y)\in A} \sqrt{(x_i - \overline{x})^2 + (y_i - \overline{y})^2} \tag{63}$$

$$\overline{x} = \int_A x dx, \overline{y} = \int_A y dy \tag{64}$$

where $(\overline{x}, \overline{y})$ can be thought of as the center of mass of the connected region under the assumption that all the pixels in the region are of equal weight and sup is supremum. Equation (62) in the main text is for measuring the regularity of a connected region. The factor $\sqrt{\pi}$ is introduced to make the measure approximate to unite. In this measure, the following factors have been considered. First, the number of indices $|I|$ approximates its area in the discrete measure in the digital image which is equal to the number of pixels for the fixed resolution on the screen. Second, n is the number of boundary pixels to describe the perimeter length. Third, R_{sum} is used to describe the distance of members on the boundary to their center. The justification of the measure is given by the bellowing:

If there is only one pixel in the region, equation (62) becomes:

$$RCGL = \frac{1 + \frac{\sqrt{\pi}}{1} \cdot 0}{1 \cdot 1} = 1 \tag{65}$$

As the region of the sampling grid approximates a disk and it becomes:

$$RCGL = \lim_{A\to\infty} \left(\frac{1 + \frac{\sqrt{\pi}}{n} \cdot \sum \sqrt{(x_i - \overline{x})^2 + (y_i - \overline{y})^2}}{\sqrt{|I|}} \right) = \lim_{A\to\infty} \left(\frac{1}{\sqrt{\pi R^2}} + \frac{\frac{\sqrt{\pi}}{n} \cdot nR}{\sqrt{\pi R^2}} \right) = 1$$

(66)

Four feature functions for a threshold level α, i.e. $NC_1(\alpha)$, $NC_0(\alpha)$, $RCGL_1(\alpha)$, $RCGL_0(\alpha)$, have been used, each of which is further characterized using the following four statistics:

$$\max value = \max_{\alpha} g(\alpha) \tag{67}$$

$$average\ value = \frac{1}{G-1}\sum_{\alpha} g(\alpha) \tag{68}$$

$$sample\ mean\ \bar{\alpha} = \frac{1}{\sum_{\alpha} g(\alpha)}\sum_{\alpha} \alpha \cdot g(\alpha) \tag{69}$$

$$sapmle\ S.D. = \sqrt{\frac{1}{\sum_{\alpha} g(\alpha)}\sum_{\alpha} (\alpha - \bar{\alpha}) \cdot g(\alpha)} \tag{70}$$

where $g(\alpha)$ is one of the four feature functions. This gives a total of 16 features based on the statistics of region content information of the image.

The structure-based region features can be applied to color space to obtain intra-plane features. A color difference representation can be used as [117]:

$$I_1 = \frac{R+G+B}{3}, \quad I_2 = \frac{R-B}{2} + 128, \quad I_3 = \frac{2G-R-B}{4} + 128. \tag{71}$$

The three features above can be concatenated to the complete feature vector for RGB image.

5.3 Experiments and discussions

The simplest basis for image classification is texture. Although its importance and ubiquity in image data is quite straightforward, a formal approach to describe the definition of texture does not exist and thus defies accurate classification at present. In this section, experiments focusing on classifications of weave patterns and their texture appearances in the fabrics will be presented. Specifically, the classification of the weave pattern is conducted in the binary-valued patterns. The classification of the texture appearance of weave pattern is performed in the gray image domain of the fabrics.

5.3.1 Weave pattern classification results

A batch of popular weave patterns (100) are chosen in order to validate the methods proposed. To investigate the essential characteristics of weave pattern, the repeated pattern is used, i.e. one repetition pattern. The three types of patterns here to classify include Plain Weave Pattern (PWP), Twill Weave Pattern (TWP) and Satin Weave Pattern (SWP). The results are shown in Figure 53, Figure 54, Figure 55, and Figure 56.

It would be difficult to sort patterns by weave type for manual classification labeling, since the taxonomy of weave patterns is controversial for some patterns. Many weave patterns fall into inevitable “miscellaneous” category. It is easier to differentiate satin weave patterns from plain weave patterns and twill weave patterns, but it is difficult to separate the latter two. As shown in Figure 53 and Figure 54, when the weave pattern complexity increases (illustrated in Figure 56) it would be a challenge to differentiate the two categories of patterns.

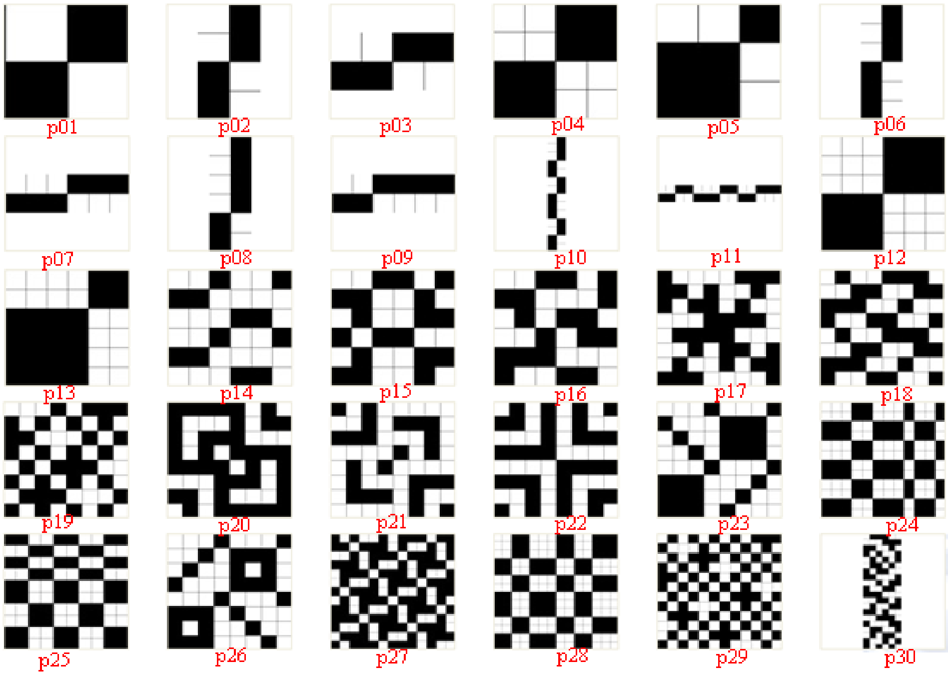


Figure 53. Classification and FFT entropy calculation results of PWP.

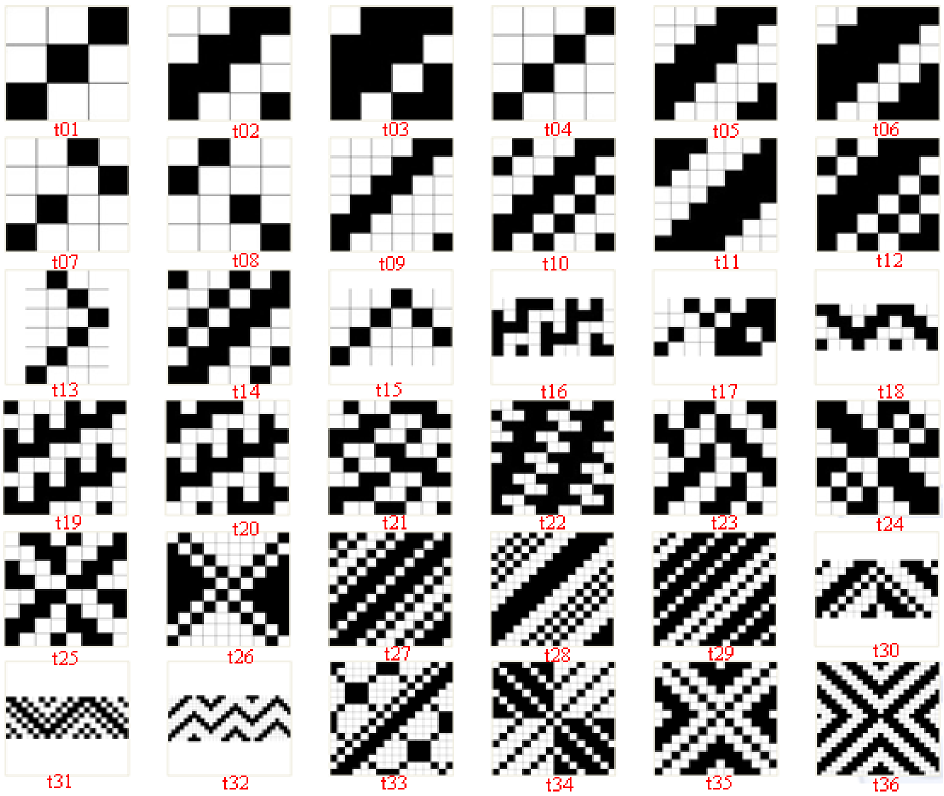


Figure 54. Classification and FFT entropy calculation results of TWP.

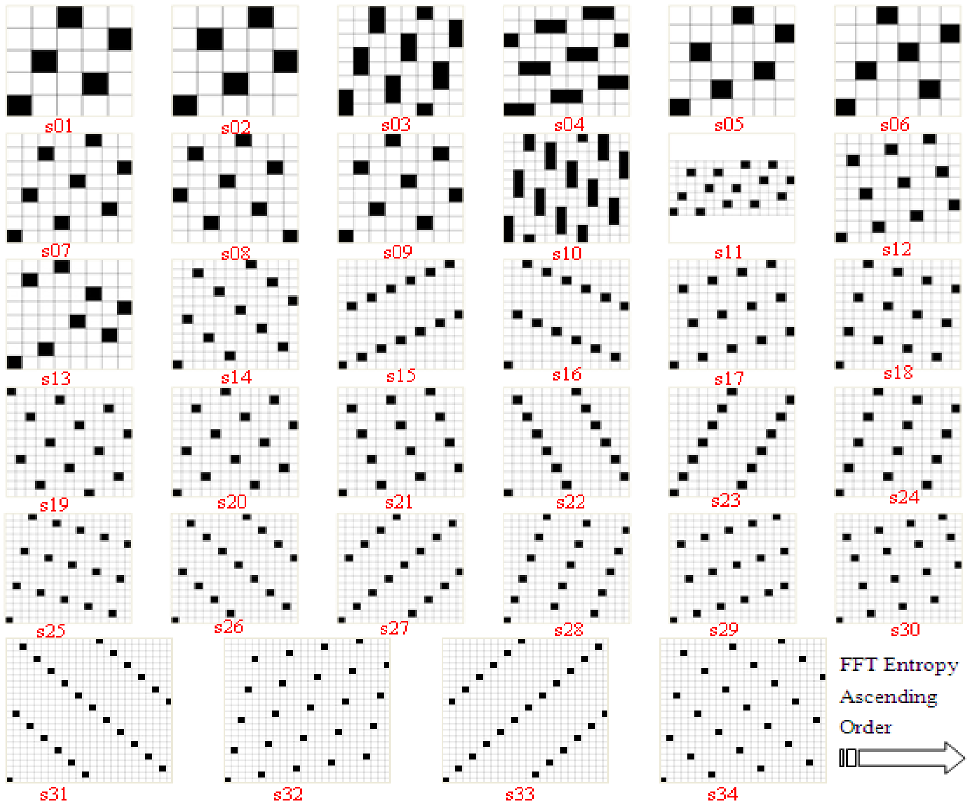


Figure 55. Classification and FFT entropy calculation results of SWP.

In the proposed classification methods, pattern definitions and pattern visual descriptors are used, such as smoothness and connectivity. The calculation results of the methods were validated as fellows. In the experiment, there are 20 designers who have at least 3-year design experience to evaluate the classification results. 18 designers totally agreed with the classification results. The other two designers had different opinions on pattern p18 and p30 in plain weave pattern category. They responded that these two should be classified into twill pattern. In fact, if there is no formal definition or an objective indexing method to describe all the variants of weave patterns, it is inevitable that different people may have different preference to classifying weave patterns. On the other hand, it also indicates the necessity of using an objective indexing method that can classify and rank weave patterns in the weave pattern database management.

From Figure 53 to Figure 55, three types of weave patterns are arranged and classified according to the three categories of patterns: plain, twill and satin patterns. Important findings are as follows. First, the ranking can be used to differentiate the number of ends/columns and the number of picks/rows. Second, similar patterns are usually neighbors. Through Fourier analysis, the measures are inherently position invariant and can extract the information of spatial arrangement of yarns inside the image (the vertical or horizontal signal response).

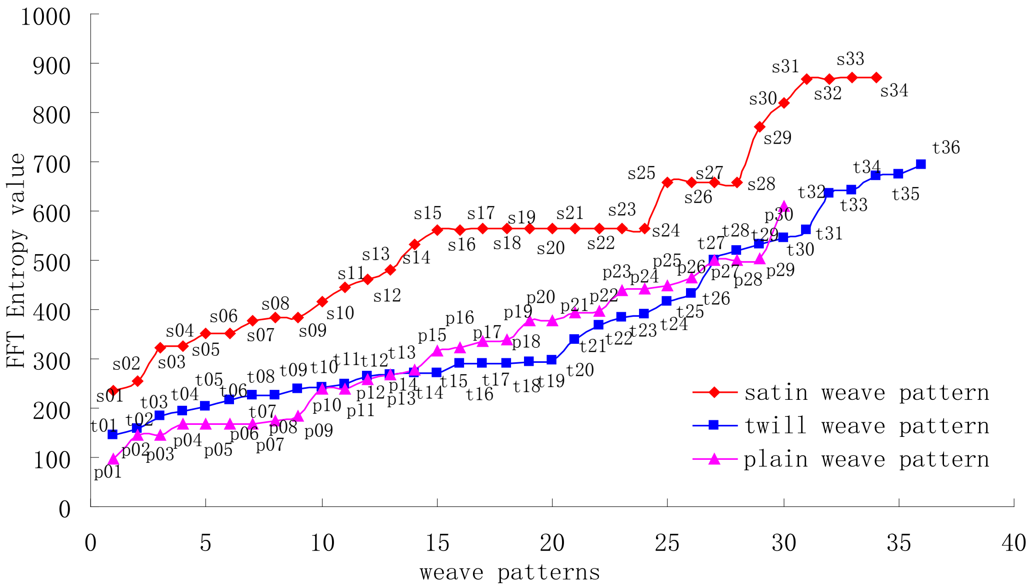


Figure 56. Classification and indexing results of different types of weave patterns.

The method is relatively immune to rotation, since order is not important in the FFT entropy calculation. As shown in Figure 56, ranking scores of samples in Figure 53, Figure 54, and Figure 55 are close to each other. For example, weave patterns of p08 and p09, p10 and p11, s17 and s18 etc. are under geometric transformations in 90° increments. The ranking scores of them are very similar. Weave patterns with the same number of warps and picks are also very close in the ranking score in Figure 56, for instance, weave patterns of t05 and t06. Ranking scores of patterns with the similar number of warps and/or picks are also close, e.g. weave patterns of s16 and s17. Therefore, it can be concluded that ranking scores of similar patterns are close in the calculation results.

In the fabric weave pattern design process, the distribution characteristics of weave point are also used to do accurate classification and indexing. This can be done by calculation of weave pattern smoothness, i.e. four-direction transitions, and connectivity, i.e. the number of warp point and/or weft point clusters. Accurate classification and indexing of weave patterns are very useful to design compound weave patterns. The distribution characteristics of weave point in compound weave patterns can be described accurately by smoothness and connectivity, which will provide navigation of weave pattern selection and matching. By using the combined methods of smoothness, connectivity and FFT Entropy, pattern similarity ranking and classification can be conducted for the convenience of fabric design and the objectivity of fabric structure evaluation.

5.3.2 Fabric texture classification results

Images shown in Figure 57 were calculated by Equations (60) and (62) respectively. The four evaluation feature functions (from Equation (67) to (70)) were applied to the image stack. All the features were standardized by their sample means and S.D.'s as follows:

$$s_i' = \frac{s_i - \mu}{\sigma},\ i = 1, 2, \ldots, n \tag{72}$$

where

$$\mu = \frac{1}{n}\sum_{i=1}^{n} s_i, \tag{73}$$

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(s_i - \mu)^2} \tag{74}$$

s_i is the feature value and s_i' is the normalized feature value; n is the number of the samples. The features calculated by Equation (60) were shown in Table 4. These features were calculated for 1-connected region, and normalization was applied to the feature values. The features calculated by Equation (62) were shown in Table 5. They were calculated for 0-connected region, and normalization was applied to the feature values.

Statistical texture features are generally easy to compute and it is considered as one of the advantages in texture description and analysis. However, they are also thought to be largely heuristic. For this reason, the single feature of the feature combinations is seldom explained in details in the previous literature. Thus, there is usually no such kind of experiment validations for each feature [59, 113, 118-123]. As a result, when those feature sets are used in the consequent classification or characterization it should be difficult to explain the physical meaning of the results. This may be mainly responsible for the nebulous explanation of traditional statistical techniques. In this study, fabric images are used to validate each feature and its ability to classify the characteristics of fabric weave patterns.

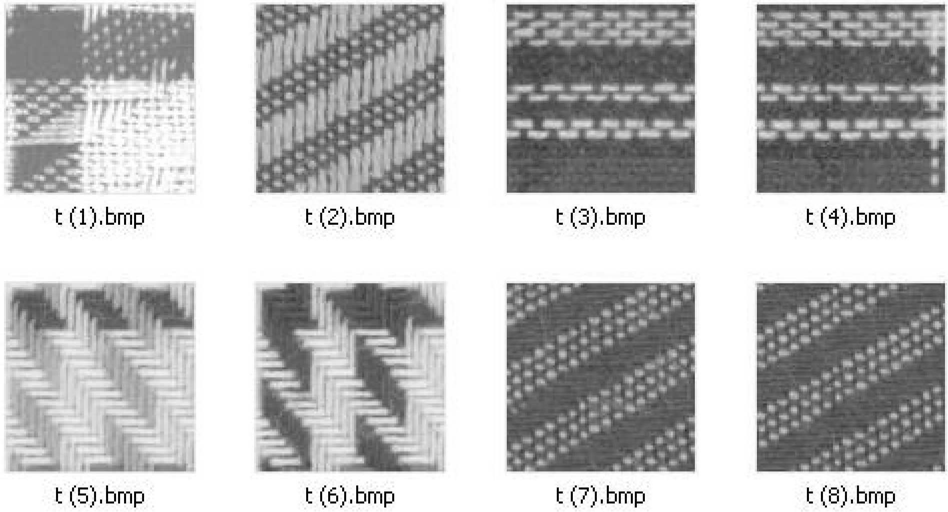


Figure 57. Fabric images for statistical feature evaluation.

Table 4. Calculation results of the statistical geometrical features (1-connected region for noc).

avg_value_irgl	sample_mean_irgl	sample_SD_irgl	max_value_noc	avg_value_noc	sample_mean_noc	sample_SD_noc
0.013518	0.957451	1.437759	-1.35389	-1.03636	1.376472	0.576148
0.092403	0.005951	-0.69459	0.677995	0.684623	0.312752	-0.96783
1.008251	-0.29314	-0.89951	-0.46389	-0.88111	-0.86219	0.438925
0.737749	0.102949	0.006922	1.114599	1.1425	-0.95549	0.212527
-0.10355	1.091467	1.526659	-0.8837	-0.99952	1.312228	-0.02588
1.12975	0.934383	0.213365	-0.8837	-0.78286	0.484371	1.831607
-1.41101	-1.34969	-0.7935	0.694788	0.865318	-0.79361	-1.08249
-1.46711	-1.44938	-0.79711	1.097807	1.007417	-0.87453	-0.98301

Table 5. Calculation results of the structure-based features (0-connected region for noc).

avg_value_rcgl	sample_mean_rcgl	sample_SD_rcgl	max_value_noc	avg_value_noc	sample_mean_noc	sample_SD_noc
2.218957	2.234602	2.177143	-1.2668	-0.73339	1.805358	0.782694
-0.06329	-0.08382	-0.22714	0.191307	1.012143	-0.0628	0.494865
-0.68635	-0.62575	-0.11361	-0.304	-1.69828	-0.78571	-0.61494
-0.8712	-0.92522	-1.06129	1.187497	1.570332	-0.73978	-0.17158
0.51213	0.403752	-0.27224	-0.85497	0.142788	1.021595	0.409559
-0.05539	0.050058	0.589146	-0.99967	-0.19567	0.409871	1.578308
-0.4263	-0.40162	-0.38513	0.898101	-0.15882	-0.79554	-1.19688
-0.62856	-0.652	-0.70687	1.14854	0.060903	-0.85298	-1.28203

The visualization of feature comparison is shown in Figure 58 and the fabric characterization results are shown in Appendix B. It can be seen that the average value of IRGL and RCGL have different fabric characterization results in Figure

58 (a). The single feature characterization results between them are quite distinct. However, there are similar characterization results of sample mean and sample SD as shown in Figure 58 (b), (c) and (d) as the shape of the characterization curve is similar. In these samples, sample 1 was considered as combination of multiple weave patterns, i.e. different weave pattern textons. The feature value of sample 1 is higher in the calculation results of RCGL by Equation (62). However, it is difficult to explain the IRGL calculation results by Equation (60). Besides, twill and plain weave patterns are ranked more closely in B2 than B1 in Appendix B. The analysis also reveals that higher ranking scores of the characterization feature were given to twill weave patterns than pain weave patterns in B2 of Appendix B.

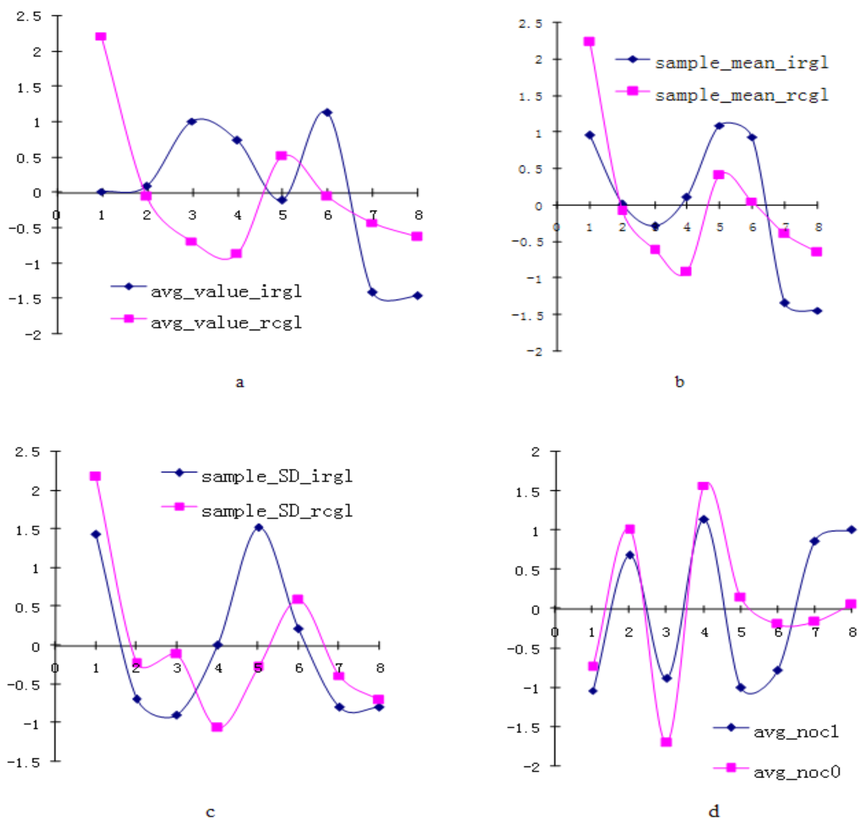


Figure 58. Feature comparison.

This study used 623 fabric images to evaluate the performance of the proposed features for fabric pattern classification. The samples included plain weave patterns, twill weave patterns, satin weave patterns, compound weave patterns, and irregular weave patterns. K-means clustering technique was used as the classification method.

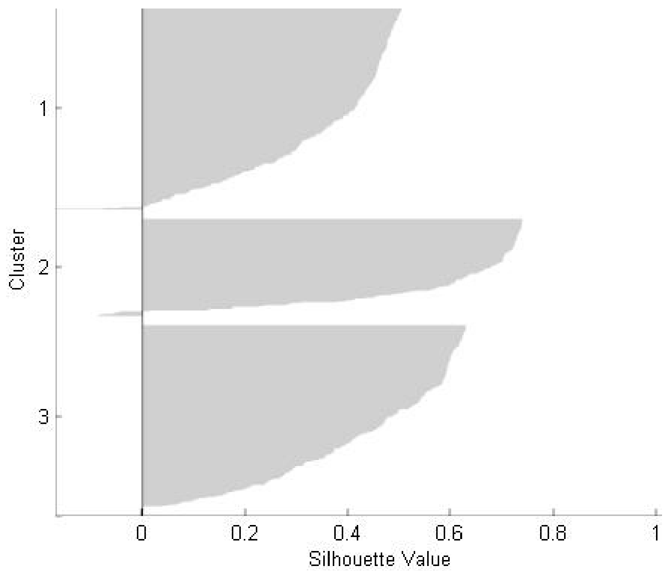


Figure 59. Clustering results (K=3).

K-means clustering is a partitioning method which partitions data into k mutually exclusive clusters. Unlike hierarchical clustering, k-means clustering operates on actual observations and creates a single level of clusters. Each cluster in the partition is defined by its member objects and by its centroid, or center. The centroid for each cluster is the point to which the sum of distances from all objects in that cluster is minimized. K-means clustering method computes cluster centroids differently for each distance measurement to minimize the sum of measurements specified.

To understand how well-separated the resulting clusters are, a silhouette plot using the cluster indices from k-means is shown. The silhouette plot displays a measurement of how close each point in one cluster is to points in the neighboring clusters. This measurement ranges from +1 to -1. +1 indicates points that are very distant from neighboring clusters. 0 indicates points that are not distinctly in one cluster or another. -1 indicates points that are probably assigned to the wrong cluster. Suppose the desired number of clusters equals to 3, the separated results is shown in Figure 59.

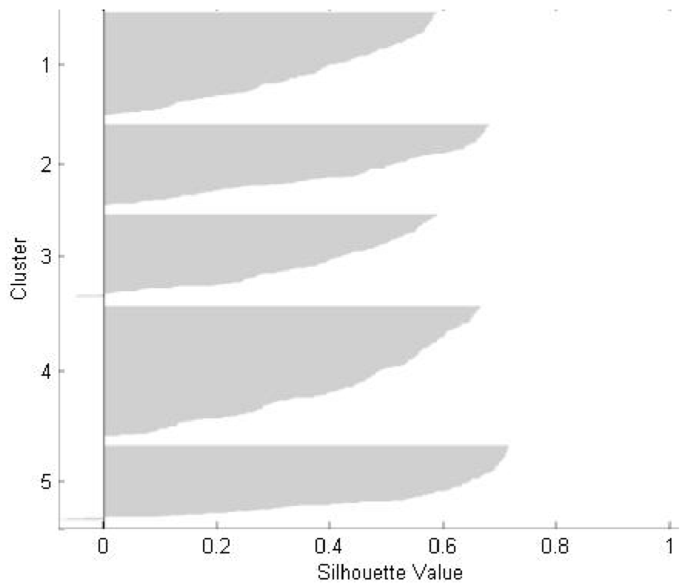


Figure 60. Clustering results (K=5).

From the silhouette plot, it can be seen that most points in the third cluster have a silhouette value around 0.4, indicating that the cluster is somewhat separated from neighboring clusters. However, the first and second cluster contain many points with low silhouette values, and even contain a few points with negative values, indicating that those two clusters are not well separated. Increasing the number of clusters can find if the clustering method is a better grouping. The clustering results are shown in Appendix C when k=4, 6, 7. The best clustering results are shown in Figure 60 when k=5. The accurate rate of classification results for five categories of fabric images are 94.2%, 86.7%, 95.8%, 90.4%, and 92.0%.

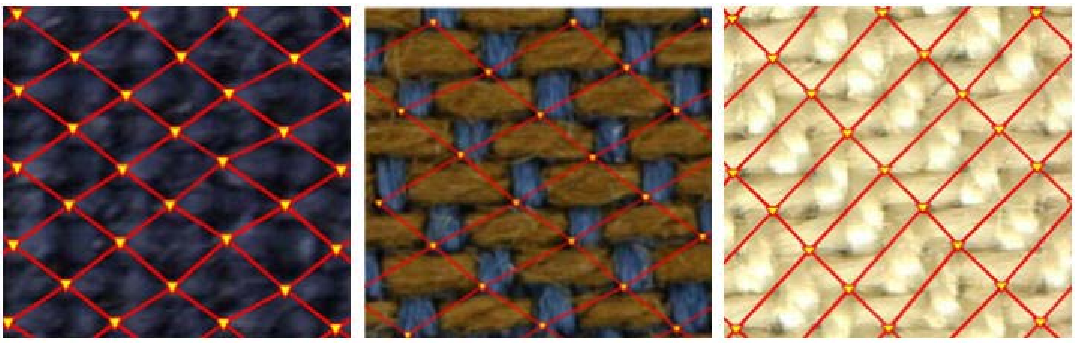
Table 6. Iterations times and total sum of distances.

Iteration times	11	11	15	10	14	30

Total sum of distances	518.7	519.3	518.7	518.7	518.7	518.7

Like many other types of numerical minimizations, the solution that k-means reaches often depends on the starting points. It is possible for k-means to reach a local minimum, where reassigning any one point to a new cluster would increase the total sum of point-to-centroid distances. A supervised method called a replication strategy is used to overcome the disadvantage. The number of times to repeat the clustering was assigned, e.g. 6 for k=5, each with a new set of initial cluster centroid positions. The final sum of distances for each of the solutions is shown in Table 6. The results show that non-global minima exist. Each of the five replicates began from a different randomly selected set of initial centroids, and k-means found two different local minima. The final solution is the one with the lowest total sum of distances over all replicates.

A statistical classification method of fabric texel extraction and inference was used to investigate high-level classification of fabric textures. The high-level classification includes two aspects. The first is the classification by weave pattern orientation and structure categories and the second by texel size and complexity.



(a) (b) (c)

Figure 61. Fabric weave pattern orientation and texel extraction. (a) plain fabric. (b) satin fabric. (c) twill fabric.

Methods of texel extraction and inference are introduced in Section 4.1.3, and the algorithm is summarized as follows:

Step I, an original image is split into two components, where u holds the geometrical information and v holds the textural information [124, 125].

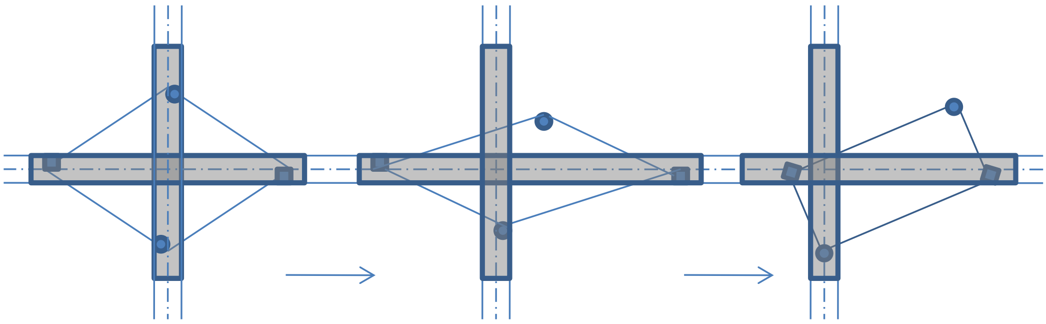
Step II, the Harris corner detector is adopted to detect low-level cues in the domain of texture information (v).

Step III, clustering techniques are then used to cluster interest points by image patch appearance.

Step IV, a MRF (Markov Random Field) model is chosen for inferring texture element locations.

As shown in

Figure 61, texels of fabrics with plain (left), satin (middle), and twill pattern (right) are extracted by using the proposed method. The shape of a texel in the red lines categorizes fabric textures into three classes.



(a) (b) (c)

Figure 62. Vertex of texel. (a) plain pattern. (b) satin pattern. (c) twill pattern.

The vertexes of the weave pattern texels in

Figure 61 are illustrated in

Figure 62. From left to right, they represent plain, satin and twill patterns. There are two findings that would help with the classification of the weave

pattern. First, the basic repetitive texture pattern does not necessarily equal to the basic weave pattern. For example, the size of the repetitive pattern is smaller than the size of the satin pattern in the second sample in

Figure 61. Second, plain and satin patterns can be considered to be the deformed quadrilateral of plain as shown in

Figure 62. Therefore, the shape of the quadrilateral can be used for fabric classification by its weave pattern and the classification method is described as follows.

As shown in

Figure 62, the plain pattern is a diamond shape and the ratio of the adjacent sides of the quadrilateral equals to 1:1 approximately. If the ratio is decreased to a number that is smaller than 1:1, the pattern becomes a twill pattern. If the ratio is further decreased, a satin pattern can be derived from a twill pattern. The threshold of the ratio can be determined by applications. Intuitively, the weave pattern classification can be implemented as a ratio selection process. The ratio of the adjacent sides for each pattern is computed in an off line manner and the classification is simply conducted by specifying a ration value through dragging a slide bar that ranges from 0 to 1 and showing up the weave patterns with similar ratio values.

In the fabric pattern selection and classification process, there are two most important factors for fabric texture designers: texel orientation and size. Weave pattern orientation and structure categories can be classified according to the ratio of the adjacent sides of the quadrilateral. In the graph design process, the motif pattern is the texel, which can be thought as an independent part of the fabric texture, for example a flower motif and a heart motif. The size of motif and the complexity of it are two of the popular classification criteria in fashion design domain. One example of categorization result is shown in Figure 63. The four fabric categories are defined and classified by the size of texel and the complexity of texel content.

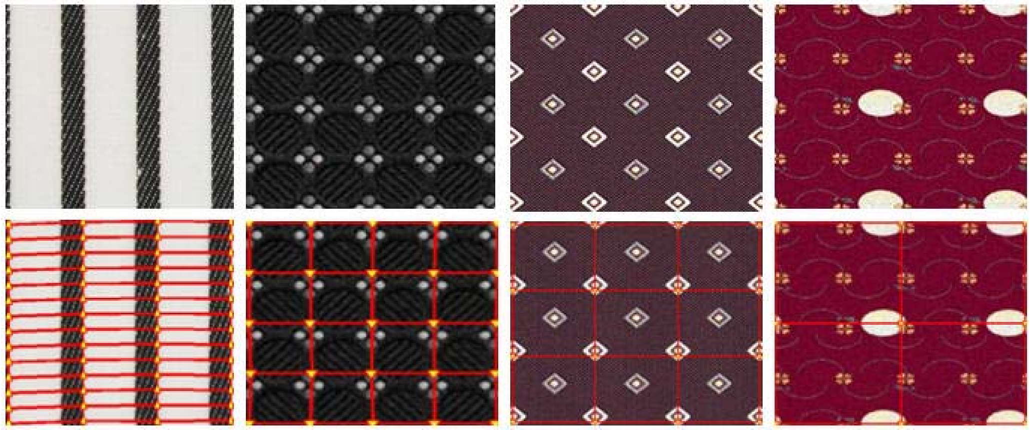


Figure 63. Fabric texture categorization.

For the size of a motif, it is usually divided into four categories, small, medium, large and extra large. The boundary of the categories is application-oriented. For example, for a shirt company, the fabric motif size is categorized into small (less than 5cm*5cm), medium (5cm*5cm~15cm*15cm), large (15cm*15cm~30cm*30cm), and extra large size (larger than 30cm*30cm).

In regard to motif complexity, there are four common classes: simple, moderate, complex, and ombre. The boundary of the classes is also application-oriented. The method of complexity indexing for a motif can refer to its pattern complexity introduced in Section 4.1.1, which is concerned about distribution of the basic features. A possible general way to calculate the basic features of motif of a fabric design is to use richness of corners and edges in the fabric texture image [126]. However, the richness of fabric texture motif is difficult to extract when the weave pattern texture is mixed with color texture of yarns, for example, the printed woven fabrics.

5.4 Summary

The first part of this chapter introduces a method of accurate weave pattern classification. First, weave patterns has been characterized into two categories according to the weave point distribution rules, namely, regular weave patterns and irregular weave patterns. Second, basic measures, such as smoothness, connectivity clustering, transitions, and FFT Entropy are used to describe and index characteristics of weave point distribution for accurate weave pattern classification.

The second part of this chapter investigates fabric texture classification based on observations and summaries of fabric texture characteristics. The analysis of fabric material-based content provides an insight to choose structure-based statistical features as a fabric texture classification method. Furthermore, a statistical method based on extraction of texel orientation and size has been used to classify fabric textures for different application purposes.

Chapter 6:

Fabric Pattern Interpolation

6.1 Definition of FPI

Fabric Pattern Interpolation (FPI) is a texture operation in which intermediate fabric textures are generated from existing ones, in an attempt to keep some texture features of the exemplars to a certain extent in the new generations. Fabric pattern, as one of the most popular man-made texture materials, includes two types of patterns: (1) weave pattern at the micro level from the point of view of structure design, and (2) figured-pattern at the macro level from the point of view of aesthetic design. As shown in Figure 1, the two are not independent but influence each other.

There are dozens of parameters for the description of fabric texture properties in the textile industry. Two most important aspects in fabric design are weave pattern and colorway. The former is the essence of structured materials and the latter concerns the warp and weft color arrangement which is considered to be one of the most significant factors to determine the motif design style of a fabric. This chapter describes and demonstrates the FPI methods in the framework of fabric texture cognitive analysis and operations.

6.1.1 Fabric pattern design

As stated in [127], designs of general woven textiles comprise three elements:

yarn, structure, and pattern. Weaving theories decide the design details of these three main elements [128]. First, the selection and arrangement of yarns comprise five main aspects: types of materials, compositions of materials, thicknesses, colors, and densities. Second, the structure designs present interlacing methods for yarns and the allotment of weaves for partial areas. Third, the two aspects of pattern designs are decorative graphics (motif) and allotted colors. These design items can technically affect each other, and must complement with each other to achieve the desired results.

There are four steps in pattern design for woven fabrics: First, design of graph motif which can be a format of painting or of digital image; second, color reduction which maps the total number of colors in the graph to colors of gamut weaves (weave pattern) [112]; third, selection of yarn color; fourth, colorway alignment. Since the weave pattern and colorway are the key components to consider in fabric pattern design process, the two are considered to be the major factors in woven fabric pattern interpolation.

Take a five- thread satin as an example of fabric pattern design source, which is generally applied with five-thread weft faced sateen and five-thread warp faced satin in fabric designing process. Thus, if the five-thread satin is designed in a whole series of weaves, the nature of its structural variation is those shown in Figure 64. New generations of weave patterns could be defined as digital gamut weaves [112] and the final color effects are determined by gamut weave type and its warp and weft color.

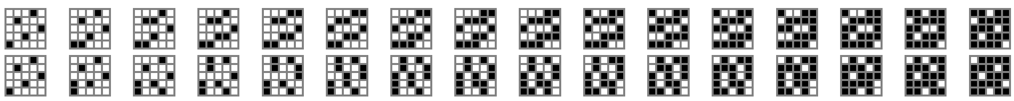


Figure 64. Gamut weaves of five-yarn satin [112].

The natural process of fabric pattern design is a typical cognitive dynamic process. There are five principles of cognition: language, intelligence, memory, and attention [129], perception-action cycle.

First, motif design is an abstract form of language to convey information and provides function of communication through element design in terms of color and shape.

Second, color reduction of graph design through gamut weave design and matching to the graph design is the essence of intelligence. The process provides two functions, noise suppressing and color dimension reduction. Multiple testes and adjustments are needed in practice and feedback is the facilitator of intelligence.

Third, selection of material (yarn and fiber material) is highly related to memory function which provides the means for predicting the actions (material production and weaving process) taken by the human cognitive dynamic system, and accounts for consequences of those actions.

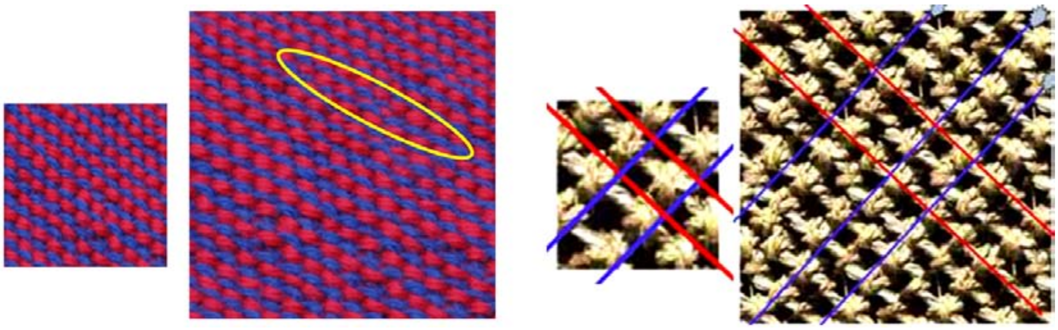
Fourth, alignment of yarn colorways in a weave pattern is the function result of attention which provides the accommodation between micro-level features (dozens of material structural parameters) and macro-level features (design motif and style). For this reason, the selection of color is one of the most difficult tasks in the design process.

Finally, the whole design process of fabric pattern is the perception-action cycle in which there have to be two parts to the cognitive dynamic design system, one part (the receiver) perceiving the environment from observables and the other part (the transmitter) acting on the environment. The perception-action cycle maximizes the information gain about the environment computed from the observables, with the information gain increasing from one cycle to the next.

6.1.2 Fabric pattern interpolation

Interpolation of fabric pattern materials is different from the texture synthesis for some natural materials (for example, sand and grass) in many previous research works, such as [84], [130] and [131]. In [84], texture interpolation was addressed and a 3D texture painting application with fabric example was illustrated. Rough cloth textures were synthesized and these images of fabric examples were produced in a low resolution and thus fabric material texture properties could not been examined. Another two examples of fabric texture generation techniques introduced in [130] and [131] were shown in Figure 65. The generated texture was assumed to be the same texture (The smaller textures were the input texture and the larger ones are the output textures).

In Figure 65, there were two problems for fabric texture synthesis. First, the structure of the output fabric texture was not consistent compared to the input. Yarns in the output disappeared suddenly and the whole structure of the pattern was thus not continuous. At the yarn level, different structures of yarn interlacing would lead to different surface appearances in the fabric texture as the material interlacing force changes the material position on the fabric surface. Second, the texture appearance of the output texture was generated by copying input. There was no explicit function that controlled the variation of weave pattern and yarn colors. The reason was that the fabric structure was not taken into account, for example, the weave pattern. Simplistically, an unlimited amount of a texel pattern should be generated through structure fingerprints with appearance variations of material units in the three-dimensional texture coordinate system in Section 3.3.1. Since the existing methods did not consider these texture parameters, these methods thus failed to provide a good solution to fabric pattern interpolation for woven fabric design.



(a) (b)

Figure 65. Texture synthesis. (a) a synthesis result by [130]. (b) a synthesis result by [131].

In this study, the design principle of fabric pattern interpolation is developed based on the cognitive dynamic system of fabric texture operations as shown in Figure 1. The framework of fabric pattern interpolation is illustrated in Figure 66. In Figure 1, fabric finger print is developed in Section 3.3 and two of the most significant elements in the feature vector of fabric finger print are proposed and adopted in fabric pattern interpolation, weave pattern and yarn color components, as shown in Figure 66.

The inputs of fabrics are divided into two sets of fabric patterns A and B and each set may contain one or multiple samples. Techniques of texel extraction, weave pattern recognition, and yarn color components selection are used to extract basic finger print elements, weave pattern and yarn color components. It is noted that the extraction of these features may need some interaction operations from the user. In this study, techniques introduced in Chapter 5 texel extraction and inference, global statistics of color attributes, and weave pattern extraction in Chapter 4 are used to generate candidates of fabric pattern finger print for pattern interpolation.

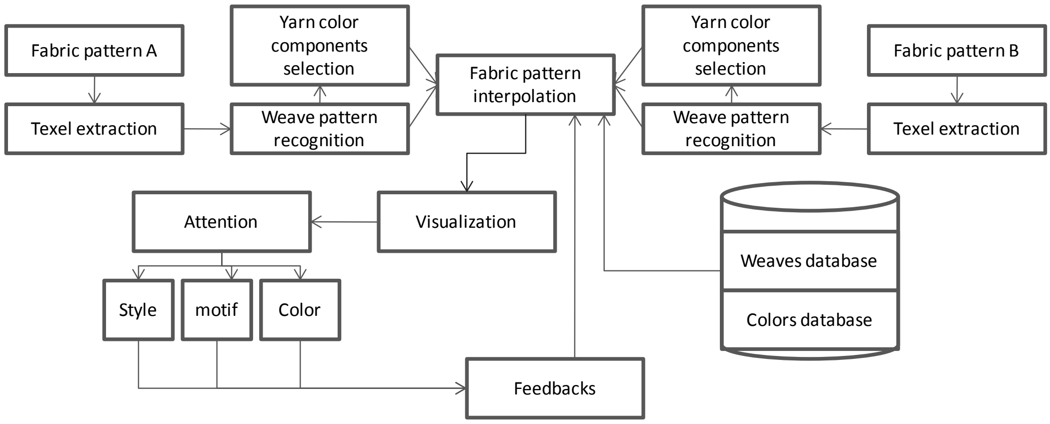


Figure 66. Framework of fabric pattern interpolation.

Evaluation for interpolated patterns is the essence of quality control of pattern interpolation. To implement the abstract functions of virtual texture manipulation engine, the design of visualization components is an important function of intermediary to collect feedbacks and move to next cycle of pattern interpolation. Feedbacks related to the basic components of fingerprint come from attention evaluation which includes style, motif, and color in fashion of the pattern interpolated. The basic finger print components to interpolate new patterns can be from the ones extracted from input fabric pattern or from database. When the extracted data from input fabric patterns communicate those corresponding data in databases, techniques of attributes representation for search or indexing introduced in Chapter 4 are used to prioritize and select basic components of fingerprint for fabric pattern interpolation.

6.2 Object-oriented database system

Color and texture are the two most important elements in fashion design. It is generally believed that certain color and texture combinations are harmonious and pleasing, while others are not. Digital fashion design and on-line communities provide new ways to investigate color and texture harmony and Object-Oriented Database System (OODS) is proposed in this thesis to study fabric pattern interpolation.

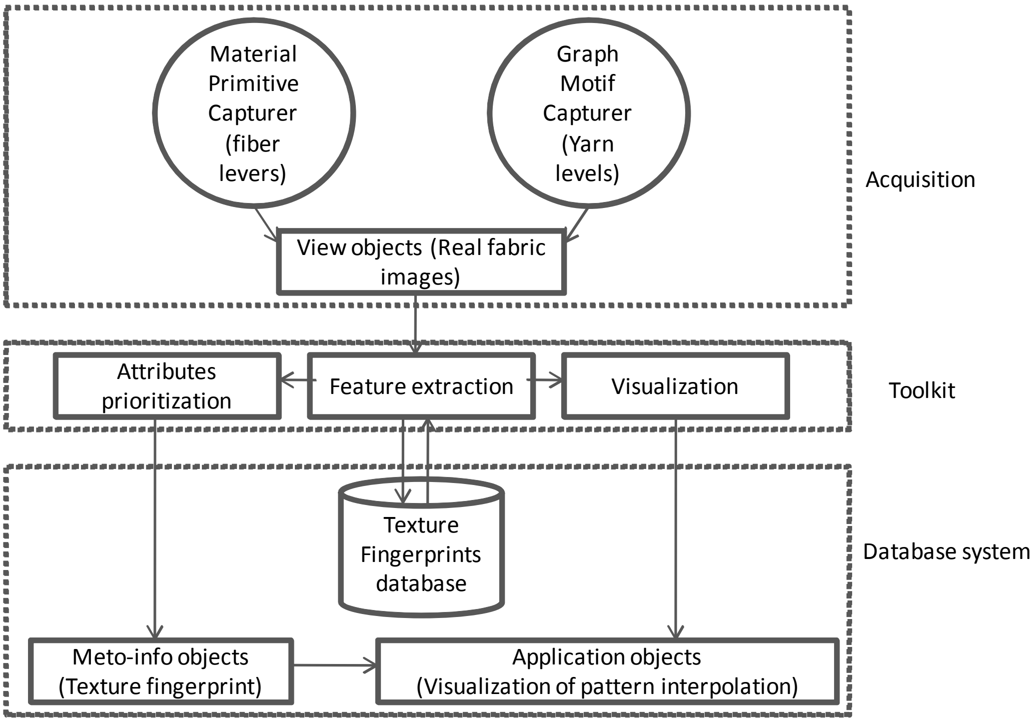


Figure 67. Object-oriented database system.

The framework of fabric pattern interpolation illustrated in Figure 66 concludes that the system includes three components, feature extraction, attributes prioritization, and visualization. The traditional techniques of texture synthesis and / or pattern interpolation based on the assumption that the relations of attributes and concepts in the cognitive informatics model for virtual texture operations are simple connections that could be fixed. It was assumed that quality / beauty of texture could be evaluated even without the context of object visualization. Therefore, those systems could not consider and build connections and perform the functions of intelligence and attention in the abstract layer of cognitive dynamic system. As a result, there is no explicit way in those systems to connect the weave pattern at the micro level and the figured-pattern design at the macro level.

Figure 68. Texture details in the application of environmental conditions.

In this study, Object-Oriented Database System (OODS) is first introduced in the texture analysis and operations system. The system of object-oriented database consists of three components, view objects (input fabric patterns), meto-info objects (basic fabric finger prints) and application objects (visualization of interpolated fabric patterns). These components are functionally corresponding to feature extraction, attributes prioritization, and visualization.

The proposed object-oriented database is the inter media to represent relations in the cognitive dynamic system for texture analysis and operations. The working mechanism of the system of object-oriented database is shown in Figure 67. Acquisition methods of material units are introduced in Section 4.2.1 of Chapter 4. Toolkit has three functions: feature extraction to generate fabric texture fingerprints, attributes prioritization to select components of fingerprints, and visualization to provide feedbacks of prioritization results of attributes. Database system is the center of pattern interpolation in the context of application and frame work of fabric pattern interpolation was shown in Figure 66. As illustrated in Figure 1, fingerprints are connections between user interface and the texture attributes. Similarly, texture fingerprints in the object-oriented database system are connecting threads in Figure 67.

The material-based content of fabric appearance is determined primarily by its distance from the viewer as shown in Section 5.2.1. Effective observation distance for texture of application objects can be evaluated in OODS, and that is the most favorite distance to examine the detail of texture. Fabric texture fingerprint developed in Section 3.3.3 is adequate for fabric texture design and production. However, it is not suitable for characterizing texture objects in effective observation distance and some of the elements in the fingerprint feature vector may not be used in a specific range of view distance. As shown in Figure 68, for instance, an individual yarn takes less than one pixel in the photo of shirts. There is no difference between the shirts with fiber texture and without. In this case, the fiber details play a minor role in determining the global texture appearance (at the figured-pattern level). This suggests that texture fingerprint for fabric pattern interpolation should be developed based on an effective observation distance in the application of environmental conditions.

The feature vector of fabric fingerprint to interpolate fabric patterns are determined by visualization feedbacks in OODS. First, feature vectors developed in Section 3.3.3 are used as the initial fingerprint feature vector in the visualization of application objects. Second, elements of the initial fingerprint feature vector are prioritized in the three-dimensional texture coordinates proposed in Section 3.3.1 for two material units (fiber and yarn) according to the score of visualization feedbacks. Note that 4 to 1 are the scores of highly significant, significant, noticeable, and not noticeable texture effects, respectively. Third, voting mechanism is used to finalize components of fingerprint feature vector for the application objects.

In the proposed fingerprint feature vector, each element is considered as an attribute for fabric pattern. The attribute is prioritized according to the indexing value of the element in the fingerprint feature vector. As shown in Figure 66, there are two sets of fabric patterns to be analyzed to provide pattern information as a baseline for fabric pattern interpolation. Application objects in the database system provide rules of priority for indexing values of elements of fingerprint feature vector. The elements with higher ranking order of the prioritization results would be used to generate new fingerprints of fabric patterns.

6.3 Weave pattern interpolation

The concept of digital gamut weaves proposed in [112] could be developed for weave pattern interpolation. Digital gamut weave is categorized into two types, warp effects and weft effects, according to the material organizational structure. In Section 5.1.2, connection and transition are used to describe the visual characteristics of fabric weave pattern and weave pattern interpolation is defined as:

$$WPt = f(WPG1 \mid WP1, WPG2 \mid WP2) \tag{75}$$

$$WPG = t(WP(i, j \pm 1)),\ for\ warp \tag{76}$$

$$WPG = t(WP(i \pm 1, j)),\ for\ weft \tag{77}$$

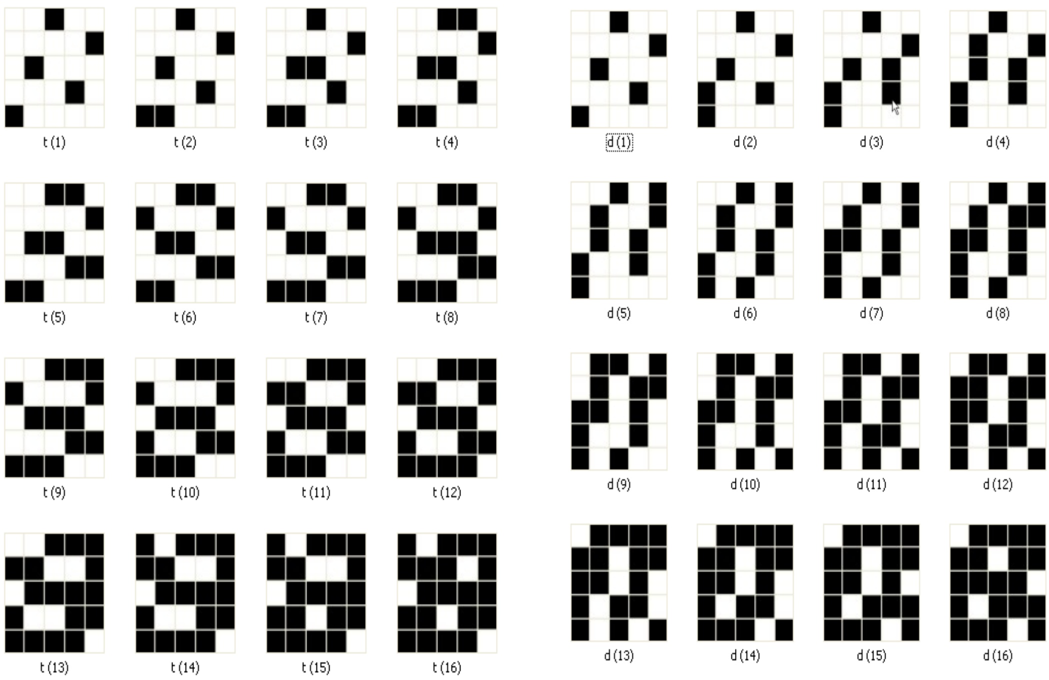
where $WP1$ and $WP2$ are the given weave pattern sets and $WPG1$ and $WPG2$ are the corresponding gamut weaves. Function t is binary flip function that changes the weft crossing point to warp crossing point, and vice versa. Function f is a prioritization function of weave patterns and the prioritized weave patterns from gamut weave set in a specified ranking range are defined as interpolated weave patterns WPt.

For a given weave pattern as shown in Figure 69, WPGs for warp and weft are calculated and generated by Equations (76) and (77). The prioritization function could be an index value of energy in the spectral domain of the weave pattern:

$$F_{u,v}e = \sum_{u=1}^{M} \sum_{v=1}^{N} (NF_{u,v})^2 \tag{78}$$

where $NF_{u,v}$ is the normalized Fourier coefficients.

Prioritization results by indexing value in Equation (78) for Gamut weaves A and B are shown in Figure 70. The prioritization results match the weave pattern interpolation rules both in warp and weft directions. Note that the indexing value of Gamut weaves A is identical to those of Gamut weaves B. This indicates that the indexing method can describe the weaves consistently (regardless of warp and weft directions). Further, it can be found that the distance between the adjacent weaves is larger at the beginning of the ranking (for example, weave 1 and 2) than at the end of the ranking (for example, 14 and 15). Intuitively, this indicates that the similarity distance of the weaves can be expressed by the indexing method.



(a) (b)

Figure 69. An example of gamut weaves.(a) Gamut weaves A. (b) Gamut weaves B.

In the experiment as shown in Figure 71, the upper part is the given pattern information and the bottom part is the application objects and the interpolated patterns in the application environment. In the upper part, the first pattern (from left to right) is the light intensity map of fabric design. The second and third patterns are input fabric patterns. A recommendation of color combination is shown in the fourth picture of the first row.

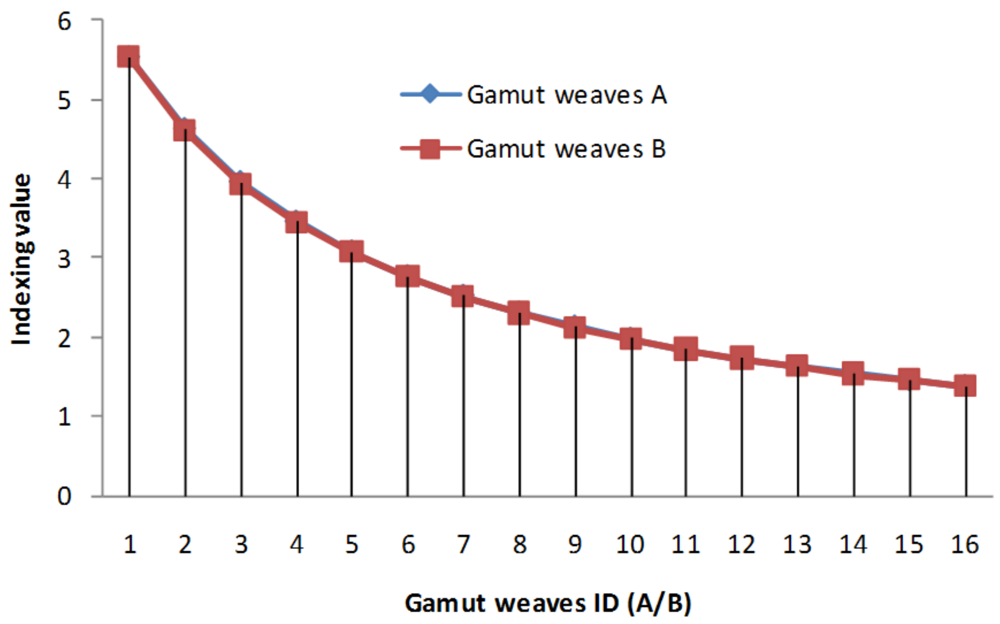


Figure 70. Indexing value of Gamut weaves A and B.

Fabric graphic design relies on effective use of color, and choosing colors is a difficult but crucial task for both amateur and professional designers. There are two suggestions, in which the color elements for pattern interpolation are determined, including colors from warp and weft colors of given patterns and color combinations from large datasets in OODS. For example, a color compatibility model and choosing colors techniques from large datasets are used to suggest color theme and color combination [132]. In Figure 71, the given color patterns consist of more than one color. Color clustering techniques could be used to extract the number of the colors and the properties of the colors inside a fabric [44]. The output of this method is a color table:

$$Color\_Table = \{Number, Colors\},$$

where

$$Colors = \left\{ Color_i = \left\{ R_i, G_i, B_{ii} \right\} \middle| 0 \le i \le Number \right\}.$$

After detection of yarn segments of the fabric in Section 4.2.2, colors of yarns can be calculated by:

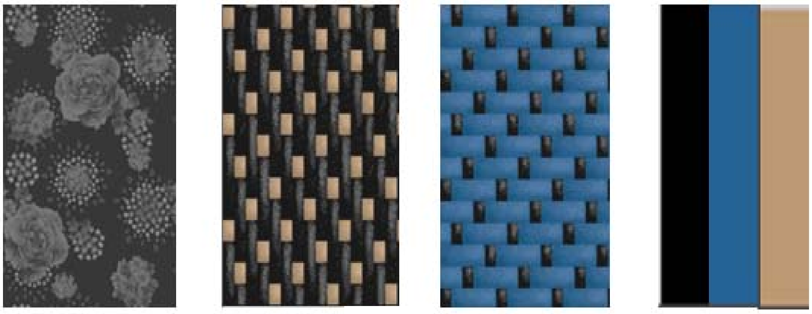
$$Color_i = \left\{ R_i, G_i, B_i \right\},$$

where

$$\begin{cases} R_i = \dfrac{1}{n} \sum\limits_{pixel_j \in E_i} r_j \\ G_i = \dfrac{1}{n} \sum\limits_{pixel_j \in E_i} g_j \\ B_i = \dfrac{1}{n} \sum\limits_{pixel_j \in E_i} b_j \end{cases}.$$

where E is the yarn segments.

Texture mapping techniques introduced in [10] were adopted in the experiments. Stochastic texture synthesis was used to generate weave pattern texture with color effects and two results are shown in the upper-middle part of Figure 71. In the bottom half of Figure 71, the first fashion manikin is mapped with the light intensity map of fabric texture, which consists of black, white, and a series of neutral grays. Fabric texture construction in a group of gamut weaves has a corresponding mapping relation in terms of light intensity gradient representation, i.e., weave texture transition in a shaded weave effects can express colored woven pattern textons in a way similar to the light intensity map of fabric design.



(a)

(b)

Figure 71. Experiment of fabric weave pattern interpolation in OODS. (a) top row: input pattern. (b) bottom row: output pattern.

Interpolated colors and textures in the two possible combinations of gamut weave in Figure 71 are shown in Figure 72. Results of fabric pattern interpolation are shown in the bottom part of Figure 71. Different figured shirts on the fashion manikin have different colors and textures in which the original textons in the light intensity map are represented by interpolated textures and colors.

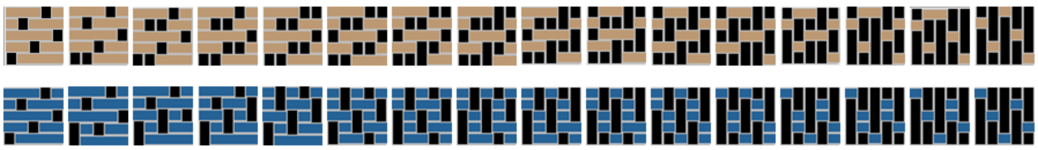


Figure 72. Interpolated color and texture pattern by gamut weaves.

It is observed that different gamut weaves would produce different weave texture and color in figured fabric pattern. The quality of interpolated patterns could be evaluated in OODS and the structure stability and color selection preference are incorporated into the system.

6.4 Colorway pattern interpolation

More than 10,000 fabric samples are collected and categorized according to fashion design. The main observations are as follows. Fabric patterns with stripe and check are the most popular designs which occupy 80% in the dataset. Garment-user preferred striped and checked patterns are far from random; color patterns form clusters or manifolds in the space of 2-5 colors and are rated with higher scores than only one color or 5 above. The findings agrees that people have strong preferences for particular colors [132]. A yarn color book from a leading fashion company comprises a collection of colored yarn tags and the utilization rate showed that there were only 100 yarn colors frequently used in the market among the total number of over 1200 colors.

The two most important elements in fashion design are determined in OODS, which are weave patterns and colorway patterns. Modern fashion designers often use photographs for inspiration when they create fabric patterns. In this study, application oriented fabric design in terms of colorway pattern interpolation is inspired and proposed in the framework of OODS.

For a photograph that is highly rated by the user, there are two issues to consider design of a fabric pattern from inspiration of the photograph. The first issue is how to select weave patterns from the weave pattern database. The second issue is regarding the extraction of the inspiration colors. In this section, weave pattern and its color map are considered as the templates. Thus, for a given weave pattern, the number of possible interpolation of colorway patterns is:

$$WPC = \sum_{r=1}^{m} P_r^i \text{ , subject to } M \in [\theta_1, \theta_2] \tag{79}$$

where WPC is the set of pattern interpolations for given colorways. m is the number of inspiration colors extracted. p is the permutation of colors for warp sequence and weft sequence. M is the Distance Measurement of Trail-Node (DM-Trail-Node) proposed in Section 4.1.2, which is used to constrain the variance of appearance. θ_1 and θ_2 are constants.

Color inspirations are extracted with an objective function which is given by [132]:

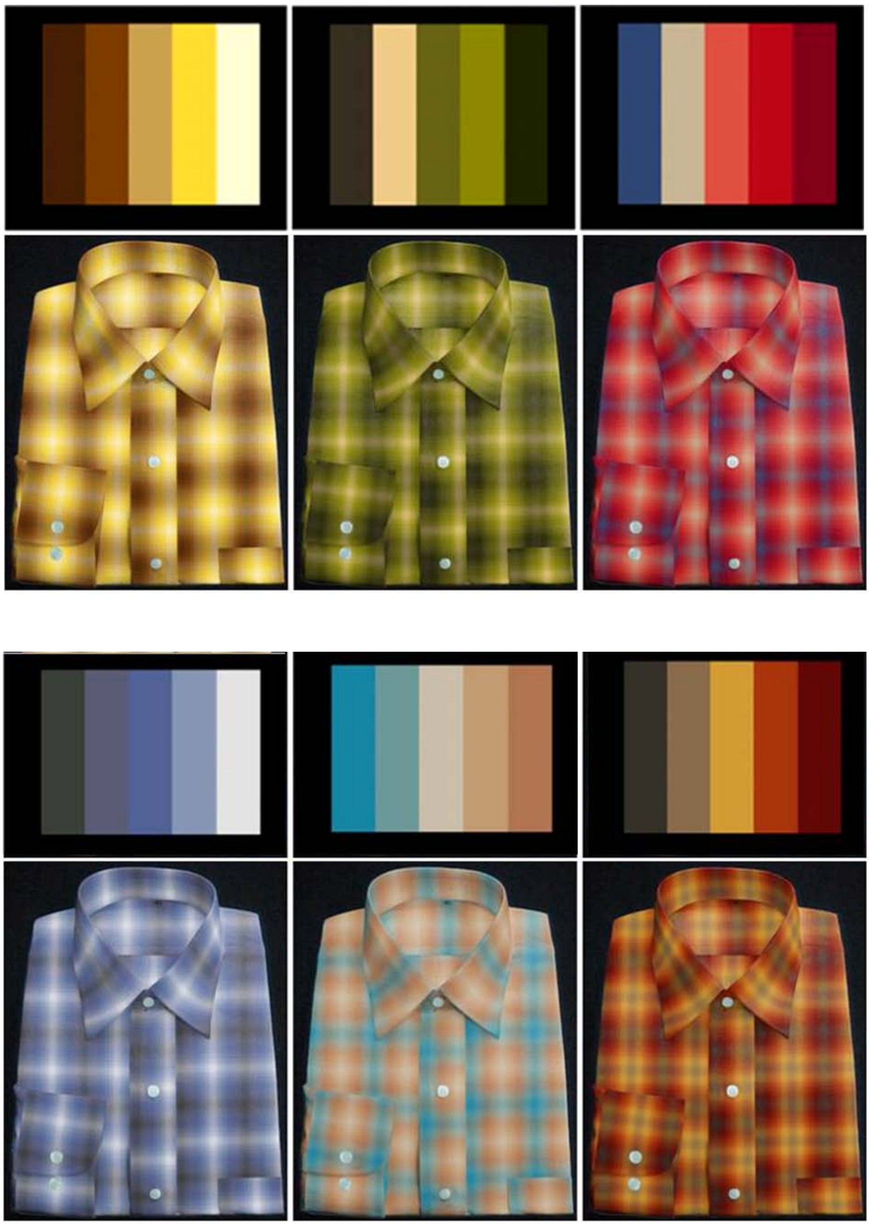
$$\begin{aligned}&\arg\min_t\{-\max_t(\alpha r(t))+\frac{1}{N}\sum_i\min_{1\le k\le 5}(\max(\|c_i-t_k\|_2,\sigma))\\&-\frac{\beta}{M}\max\sum_{j\in N(t_k)}\max(\|c_i-t_k\|_2,\sigma)\}\end{aligned}\tag{80}$$

where c_i is a pixel color, t_k is a color combination, and N is the number of pixels. The first term measures the quality of the extracted color combination. The second term penalizes dissimilarities between each image pixel and the most similar color t_k in the color combination. The third term penalizes dissimilarities between color combination t_k and the M most similar image pixels $N(t)$. α, β, and σ are constants.

Experimental results are given in Figure 73. Six raw pictures, including natural scenes and paintings, from [132] are used to extract the color themes by using Equation (80) and then applied to the colorways of weave patterns. As a result, six sets of ties and shirts are generated through the extracted color themes. The experimental results show a possible way to produce a batch of designs with the given weave patterns. In fact, it is one of the most common design methods in garment design and these designs could be easily found whenever one goes shopping for garments, such as shirts and ties.

(a)

(b)



(c)

Figure 73. Colorway pattern interpolation through cognitive color theme. (a) color themes and fabric patterns on ties. (b) color themes and fabric patterns on ties. (c) fabric patterns on shirts.

6.5 Texture interpolation of Jacquard pattern

A weaving system is designed to automatically maintain a graph pattern in alignment with woven texture and it would be helpful to automate that process by texture interpolation through computer vision techniques. For decades, Computer Graphics (CG) has played an important role in many kinds of design works, especially, industrial design of solid objects. However, most available methods cannot work well for soft and deformable object like cloth [133].

The motivation of texture interpolation of Jacquard pattern is that the designs of cloth pattern could be evaluated or modified in the proposed OOBS framework before they are sent to weaving control system and produced on weaving machines. The study of texture interpolation of cloth is meaningful because of the significance of efficiency and cost. Based on those considerations, texture interpolation techniques for cloth and OOBS framework are proposed to simulate human cognitive design process in practice and daily life. Following examples demonstrate applications of texture manipulation techniques of computer vision and graphics to Jacquard pattern interpolation.

6.5.1 Weave pattern synthesis

Weave pattern is the texton of cloth structure and it is necessary to start with texture samples of weaves in cloth and then evaluate the applications in the virtual environmental world with appropriate view distance and texture details as discussed in Section 6.2.

There are two possible ways to generate texture samples of weave patterns for Jacquard cloth due to the physical structural limitations and, in the end, beauty principles as described in the latest study of Jacquard reinventing [112]. One is example-based texture images from real cloth and the other is pattern-based texture modeling by computer graphics techniques.

Examples in Figure 71 illustrate that simple techniques of stochastic texture synthesis might be applied to pattern-based texture construction with basic parameters, such as average intensity levels and their contrast with distributions based on Peirce model [134]. The virtual cloth on shirt and mankind presented in Sections 6.3 and 6.4 looks even better and more natural than complicated algorithms, for instance, in [135], thanks to the comprehensive studies of fabric texture to understand material units and texture patterns of fabrics.

Additionally, in this section, a method for fabric texture synthesis using example-based approach is introduced to generate texture samples of weave patterns which are larger than the input ones. Texture generation is one of typical computer graphics applications that arise whenever one attempts to apply example-based textures to generate large textures for rendering of complex graphics scenes.

A matching quality to measure difference between the pairs of pixels needs to be defined. The problem can be easily formulated by the bellowing equation [136]:

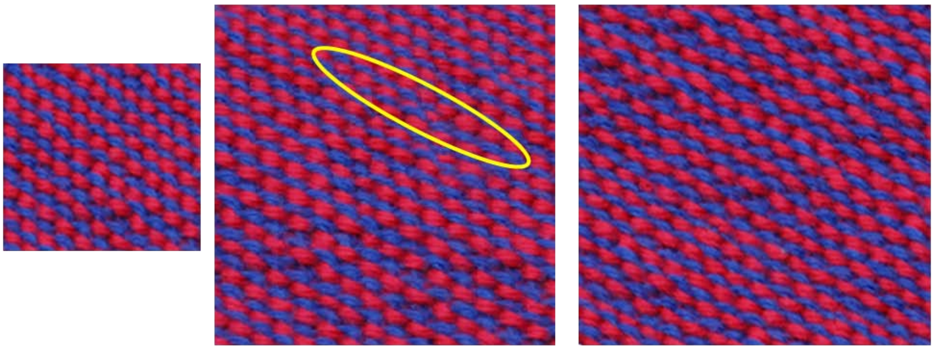
$$M(s,t,A,B) = \|A(s) - B(s)\| + \|A(t) - B(t)\| \tag{81}$$

where A and B are the patches to synthesize; $A(\cdot)$ and $B(\cdot)$ are the pixel colors for given position in the new patch to be synthesized and the existing patch; s and t are the two adjacent pixels copied from patches. The equation defines the matching quality cost M between adjacent pixels, and an appropriate norm is used for different types of texture classes.

Entire patch placement is suitable for structured textures [130]. To account for partial overlaps between the existing and new texture patches, the sum-of-squared-differences (SSD) cost with the area of the overlapping region are normalized and the cost for all possible translations of the existing texture is given by:

$$C(t) = \frac{1}{A_t} \sum_{p \in A_t} \left| Nt(p) - Et(p+t) \right|^2 \qquad (82)$$

where $C(t)$ is the cost at translation t of the existing texture for a given color channel, Et and Nt are the existing texture and new texture to add, and A_t is the portion of the translated Et overlapping Nt. The target is to make the cut between two overlapping patches on the pixels where the two textures match best. This can easily be done with dynamic programming.



(a) (b) (c)

Figure 74. Fabric texture synthesis results. (a) input fabric pattern. (b) the synthesized result by [130]. (c) the synthesized result by the proposed method.

Skew detection techniques, such as yarn location detection introduced in Section 4.2.2, are used to calculate the placement orientation for texture samples of weave patterns. The ideal placement of texture sample is that the warp is in vertical direction in the image and weft in horizontal. The weft direction and warp direction could be detected and adopted as the heuristic to choose the optimal graph cut.

Since fabric is more structured in weft than warp as described in Section 4.2.2, it is desired to start calculating weft direction overlapping SSD and then refine the candidates using the warp direction overlapping SSD, instead of calculating the sum of the two original image directions in [130]. The comparison of the proposed method and [130] for fabric texture synthesis is shown in Figure 74. The left image is the example texture, the middle is texture synthesis result by method of Efros and Freeman, and the right is the result of the proposed method. In fact, the cracks could be removed by graph cut techniques as used in [136], instead of dynamic programming. However, the cost of the algorithm complexity increases which would reduce the efficiency of the performance.

6.5.2 Fabric phase image

Given a graph design, the target of Jacquard pattern interpolation is to transfer characteristics of woven fabric texture into the phase image through appropriate placement of fabric gamut weaves with proper colorway alignment of warps and wefts. A phase image is one kind of graph designs in which the number of colors is designed to be the same as the number of regions in the phase image. The graph designs are usually paintings on paper. The graph design by hands may show clearly the outline or profile or boundary and it also has special texture in painting.

Texture in painting is a difficult element to define. It does not just refer to the roughness or smoothness of a work of art, but also to the subtle gradations of surface difference, from the quality of the brushstrokes to the addition of foreign elements into the work of art as shown in Figure 75. The most exciting aspect of texture is that, when used carefully, it adds to the meaning and depth of an artwork. On the other hand, if texture is used inharmoniously, it can become a negative factor.

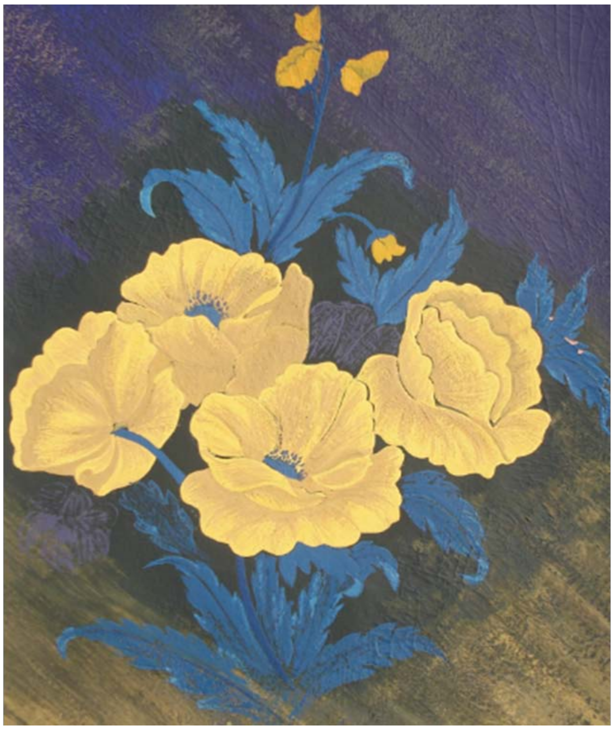


Figure 75. A painting by the author in 2002.

It is challenging to deal with both fuzzy texture and sharp object in image processing. Recent methods of image segmentation using fuzzy region competition [137, 138] can be used to solve the problem of texture and object separation in painting. The merit of fuzzy region competition is that the optimization problem is convex with respect to the membership function which ensures that the method is insensitive to the initialization, and that the global minimum can possibly be found, in addition to its higher efficiency benefiting from adoption of Chambolle’s projection algorithm [139]. Since spatial region information and frequency region information in an image is application-dependent, the parameters of spatial and frequency functions in [137] need to be tuned based on prior knowledge for different design styles of paintings. For general image processing, algorithms proposed in [140] are used in the experiments.

Specifically, the region segmentation in this study mainly follows the method in [140] except for converting the image from RGB channels to CIELAB. Let Ω be the bounded Lipschitz domain, $\mathbf{I}(\mathbf{x}):\Omega \to \mathbb{R}^3$ be a color-scale image, and each component of $\mathbf{I}(\mathbf{x})$, $I_j(\mathbf{x})\ (j=1:3)$, corresponds to the representation of the three channels in the CIELAB space. It is assumed that the domain Ω can be partitioned into N sub-regions, $\Omega_1,\ldots,\Omega_N$, along an edge set $\{\partial\Omega_i\}_{i=1:N}$, such that $\bigcup_{i=1}^{N}\Omega_i = \Omega$ and $\Omega_i \bigcap \Omega_j = \Phi$ for $\forall\, i \neq j$, $i, j = 1:N$.

The segmentation model of fuzzy region competition of minimizing the energy functional is given by:

$$E(U,a) = \sum_{i=1}^{N}\int_{\Omega}|\nabla u_i|dx + \lambda\sum_{i=1}^{N}\int_{\Omega} r_i^{a_i} u_i{}^p dx \tag{83}$$

subject to:

$$(i)\ \sum_{i=1}^{N} u_i = 1, \qquad (ii)\ 0 \le u_i \le 1,\ for\ i = 1:N \tag{84}$$

where N is the number of regions; u is the fuzzy membership function; the term $\int_{\Omega}|\nabla u_i|dx$ equals the perimeter of region Ω_i; $a=(a_1,...,a_N)$, $r_i^{a_i}$ are error functions in region Ω_i, which equals to $|I-c_i|^2$, and $a_i = c_i$ are constants (in the case of fabric images, the model to local case is used [140]); ∇ is the gradient operator; λ, p are positive parameters to determine the fuzziness of segmentation.

For the efficiency of minimizing the energy equation above, i.e. Equation (83), a fast total variation minimization method is chosen to solve it [141] and take use of Chambolle's fast dual projection algorithm [125]. The alternative minimization method to minimize energy E is used to region parameters, auxiliary variables, and membership function.

6.5.3 Chinese brocade interpolation patterns

Chinese brocade is a kind of figured fabric originated from ancient China, in which multiple wefts are employed in conjunction with one series of warp threads. All the wefts are floating on the surface as required in producing the figured effect and to assist in providing the ground structure as shown in Figure 76. Therefore, the brocade fabric is a kind of weft figuring fabric with an intricate weft-backed or multi-layer structure. It was the highest achievement of silk fabrication in ancient China and is still being well-received in the world market today [112].

Traditional Chinese Brocade design method was extended by digital design technologies and the color mixing design principles were introduced in Jacquard design. Gamut Weaves design method in [112] is used as the pattern interpolation rule in this study.

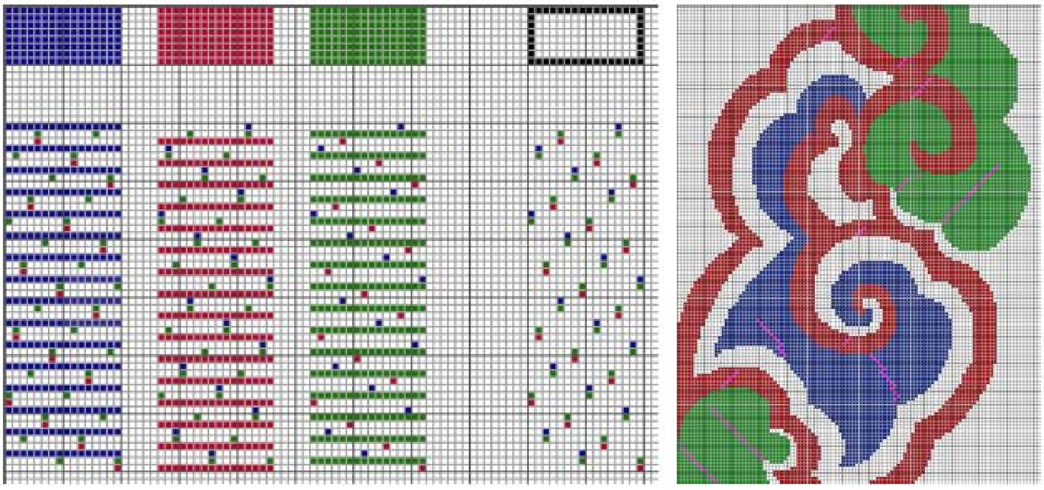


Figure 76. Structure design for Chinese brocade with three wefts [112].

A weave pattern matrix Ψ is rewritten as its absolute weft effect matrix format in which the weft float region is larger or equal to the warp float region (in the same way, warp effect matrix format can be defined):

$$\Psi weft = \Theta weft(\Psi) \tag{85}$$

where functional $\Theta weft(\cdot)$ is the operation functional. Suppose Ψ is warp effect pattern, the operation functional is given by:

$$\Psi weft = \left[\Psi \mid \Psi_{i,j} = 0,\ for\ \Psi_{i,j} = 1; \Psi_{i,j} = 1,\ for\ \Psi_{i,j} = 0 \right] \tag{86}$$

The independent variable of functional $\Theta weft(\cdot)$ is the same as the dependent variable when Ψ is a weft effect pattern. To represent the interpolation functional, first a set of matrices $\mathrm{E} = [E_1, ..., E_t]$ is constructed in which each has the same dimension to Ψ and iteration functional $R(\cdot)$ which controls the element of matrix in E and the time sequence in E. Note that Gamut weaves of $R(\cdot)$ usually takes the formats of formulae in (76) and (77) for warp and weft directions respectively. In this case, the interpolation functional could be represented as:

$$f = f(\Psi, E, R) \tag{87}$$

There are many ways to generate the Gamut weaves (see examples in Appendix) and the evaluation function to measure the distance between two possible neighbors of candidates could be equations (16) and (78). In addition, LBP (Local Binary Pattern) techniques [142] could also be used to describe the candidates in terms of spatial and frequency domains.

6.5.4 Two-level synthesis of interpolation patterns and applications

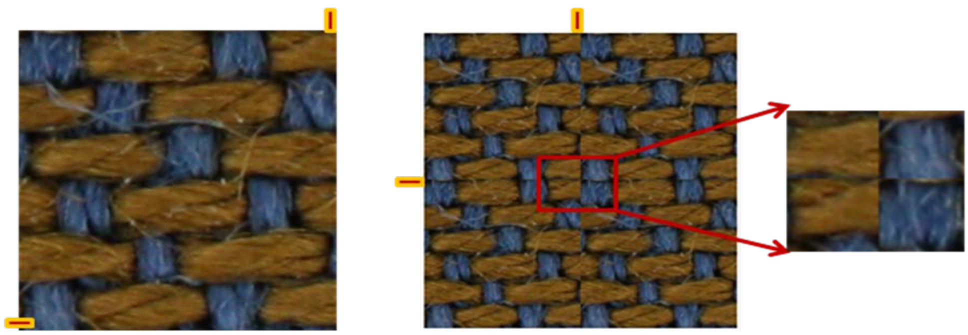
There are two major components in FPI, the graph design (phase image) of the motif and weave pattern design of material units. The graph design is to generate a phase image wherein different regions are labelled for colorization. Weave pattern design is the process of material alignment in spatial domain. It is necessary that both components are available. The former determines the global pattern, whereas the latter generates the local pattern. Good design has the feeling of a unified whole, in which both components in FPI are in balance and harmony. A two-level texture synthesis method is proposed for FPI based on weave pattern interpolation functions and phase image extraction. Two levels of texture synthesis are weave pattern level and phase image level.

At the level of weave pattern, texture synthesis was conducted as follows. First, graph cut techniques in Section 6.5.1 is applied to generate a seamless texture which is larger than the input sample. Graph cut techniques solved the cracking of the boundaries by a min-cut technology. A fabric sample is shown on the left in

Figure 77. A tiling image of the input sample is given on the right. A new

synthesized fabric pattern by graph cuts is shown in Figure 78. Second, fabric structure recognition techniques in sections of 4.2.2 and 4.2.3 are adopted to obtain the weave pattern map. Third, an active-grid-model in spatial domain was used to segment the synthesized fabric pattern at the yarn level [44]. Fourth, weave pattern interpolation techniques in Section 6.3 and Section 6.5.3 were adopted to generate gamut weaves of the synthesized fabric pattern. Output of weave pattern synthesis results are shown at the bottom in Figure 79.

There are two methods to generate fabric gamut weaves of the fabric weave pattern. As shown in Figure 80, fabric gamut weave (a) is generated by copying and stitching warp floats. The blue color regions are warp yarn floats. Two identical warp floats are stitched side by side. Fabric gamut weave (b) is generated by randomly choosing warp floats and stitching to original warp floats. The synthesized result looks more natural as fiber details are more irregular on the fabric surface. The first method is used to generate yarn details in low resolution fabric image, whereas the second method is used to obtain fiber details in high resolution fabric image.



(a) (b) (c)

Figure 77. Fabric texture synthesis by tiling method. (a) input sample. (b) tiling image. (c) cracked boundaries.

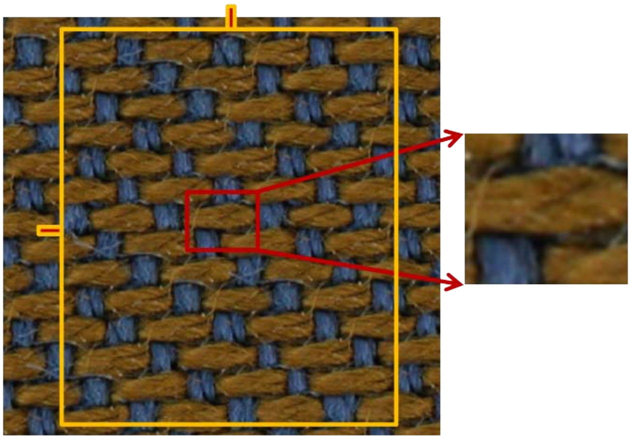


Figure 78. Smooth boundaries by graph cuts.

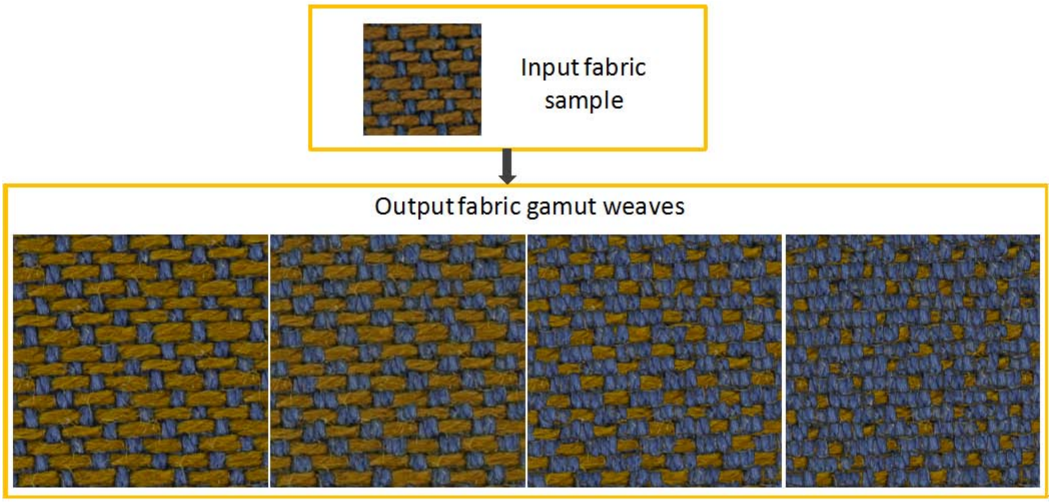
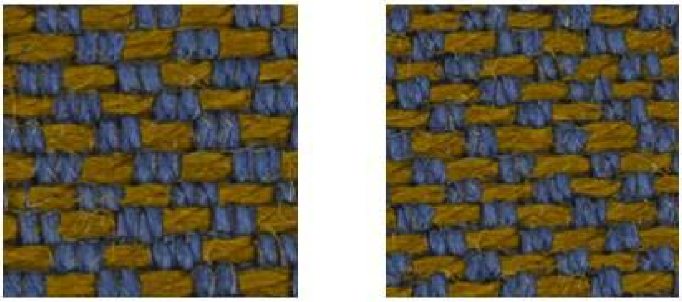
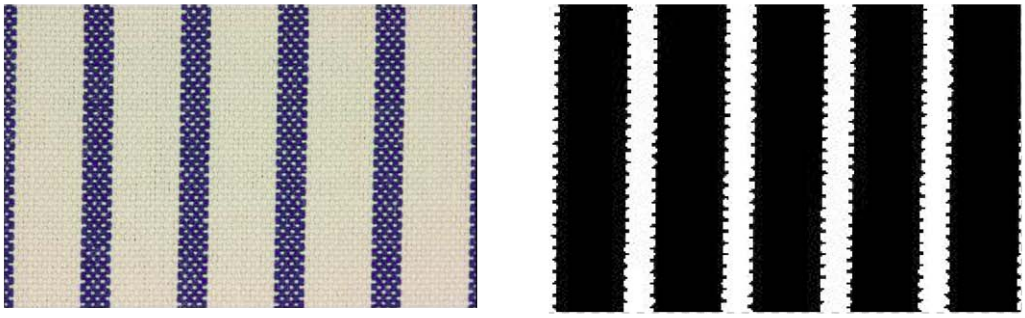


Figure 79. Gamut weaves generation.



(a) (b)

Figure 80. Yarn floats generation. (a) identical adjacent floats. (b) different adjacent floats.



(a) (b)

Figure 81. A fabric sample and its two phases image. (a) input sample. (b) output phase image.

There are two ways to obtain a phase image. The first way is to use a fabric image and segment it into different phases based on colors of yarn floats. In

Figure 81, a fabric image is given on the left. Its phase image is obtained by MAP-ML estimations since it is efficient to deal with rough texture areas [143]. The second is to use a painting and do segmentation on it to obtain the phase image. A painting image is necessary for Jacquard fabric design. The painting is usually drawn by hand and much noise is introduced. A painting with a flower motif for Jacquard fabric design is shown in Figure 75.

Two-level synthesis of interpolation patterns is carried out for Dobby fabric pattern shown in

Figure 81. From a given weave pattern, its textures are transferred to the phase image by putting the gamut weaves of the given pattern onto different regions of the phase image. The fabric sample in Figure 79 is used as an input weave pattern. The gamut weaves are applied to the phase image in

Figure 81. The output synthesis results are shown in Figure 82. The correspondence of textures between gamut weave patterns and the input fabric sample are used. The features may include color, brightness intensity, local regional orientation and coarseness.

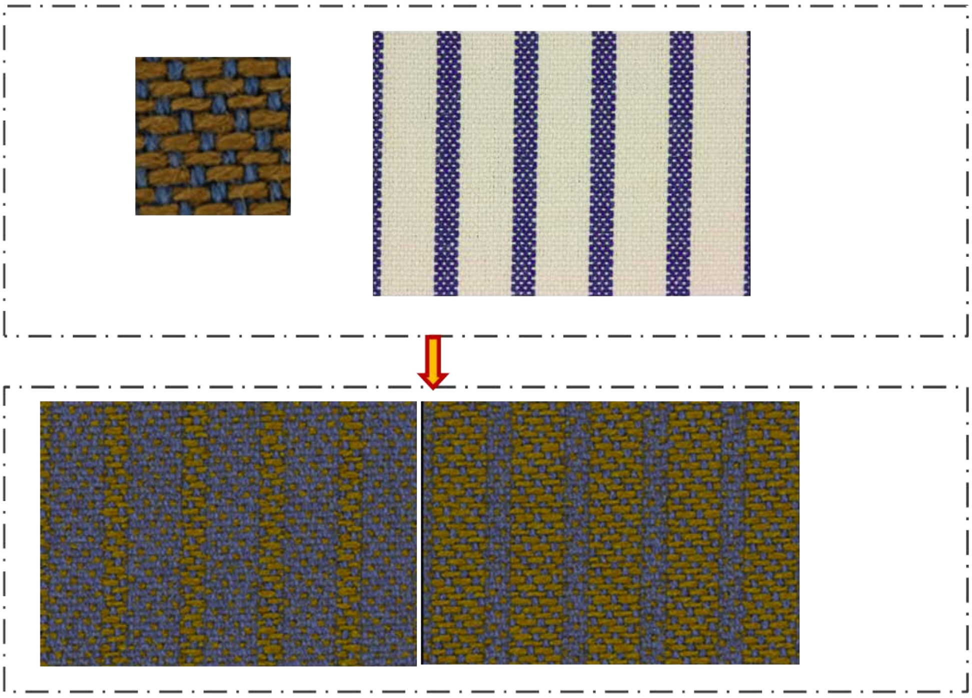


Figure 82. Fabric synthesis results by interpolation patterns.

In Figure 82, brightness intensity is used to generate the correspondence. The first output weave pattern in Figure 79 is used to fill the regions with low brightness intensity of the phase image in

Figure 81. The last output weave pattern in Figure 79 is used to fill the regions with high brightness intensity of the phase image. The synthesis result is shown on the right in Figure 82. A new synthesized fabric pattern is obtained by changing the filling order. The result is shown on the left in Figure 82. The regions with high brightness intensity in the phase image are filled by the last output weave pattern in Figure 79. The regions with low brightness intensity in the phase image are filled by the first output weave pattern.

The painting shown in Figure 75 is used for Jacquard fabric synthesis. Since the painting contains both coarse and fine textures, a fuzzy multi-region competition segmentation technique in Section 6.5.2 is used to obtain its phase image. The rest of the synthesis method is conducted in the same way as Dobby fabric synthesis. The best number of phases in the painting depends on needs of applications. For example, if the style of the fabric needed is of simple and abstract, the number of phases is usually two or three. A simple Jacquard fabric synthesis result is presented in Figure 83 (a) in which the number of phases is three.

In Figure 83, gamut weaves with the same color values of yarn materials are used in fabric (a). The gamut weaves create little difference between the background and regions of the fabric. Leaves in the painting almost could not been discriminated from the background. The colorway pattern interpolation techniques in Section 6.4 are used to change the color values of yarn materials. A series of fabric textures with different colors are generated, as shown from (b) to (f). Different colors of yarn materials create different textures in the fabrics. The color plays a role of changing appearance in Jacquard fabrics. For instance, the textures of the flowers in (e) and (f) look different. Different warp yarn color and weft yarn color are taken into account for explaining the difference.

The details of Jacquard fabrics could be augmented by using more gamut weaves. A fine fabric result is shown in

Figure 84. The fabric has similar colors and textures to the original painting. The gamut weaves are generated by simple stochastic texture synthesis techniques. Gamut weaves with low resolutions in the Jacquard fabric look realistic. Displaying of gamut weaves in Jacquard fabric is influenced by the texture resolutions.

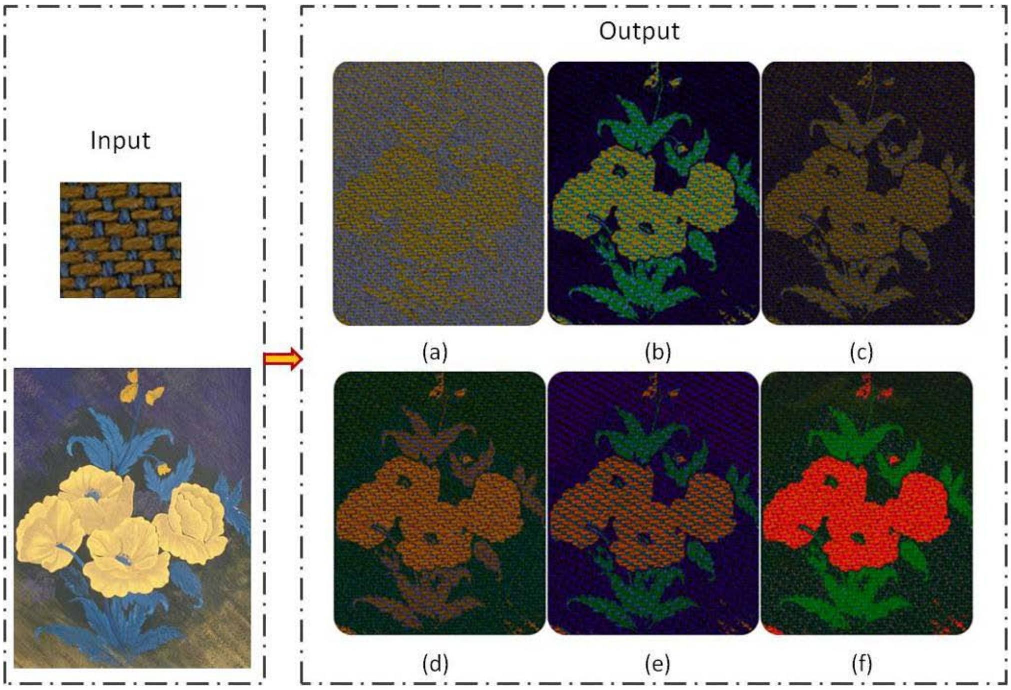


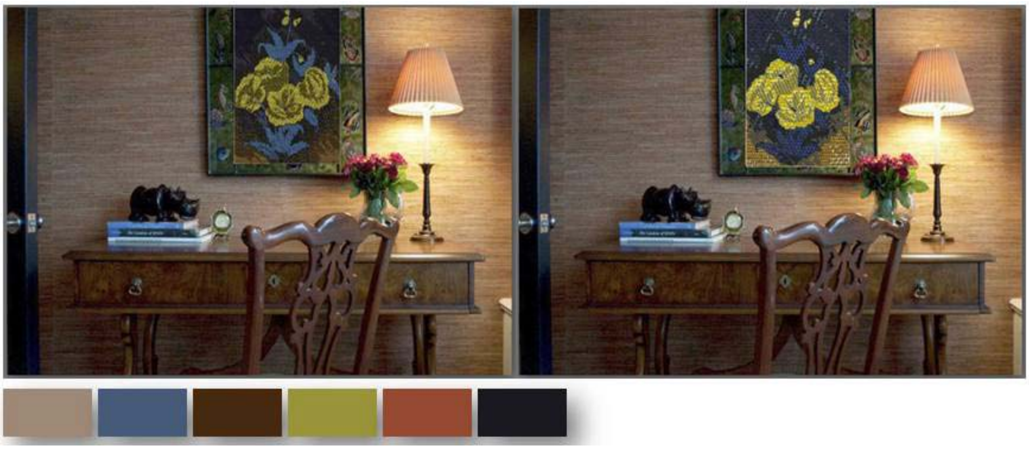
Figure 83. Jacquard pattern synthesis results with different colors by weave pattern interpolation and phase image extraction.

(a) (b)

Figure 84. Adding details by extracting more phases of the image. (a) synthesized result. (b) original image.

(a) (b)

Figure 85. Synthesis result from real fabric images. (a) synthesized result. (b) original image.



(a) (b)

Figure 86. Different synthesized styles of Jacquard tapestry in an application environment. (a) fine texture. (b) coarse texture.

In a similar way, the real fabric images are used to synthesize the Jacquard fabric. Gamut weaves are selected by color and texture from the fabric library. The same phase image is used and the synthesized result is shown in Figure 85. In the textile manufacturing process, it is natural to use the specified materials to produce new fabrics with different graphic designs. It will be very useful to map fabric textures onto objects in application environments.

(a) (b)

Figure 87. Synthesized cloth on human body. (a) synthesized results. (b) fabric pattern details.

As shown in Figure 86, the Jacquard fabrics in

Figure 84 and Figure 85 are used in an example of interior decoration. Fabric textures in Figure 82 are mapped onto a manikin and the shirts are displayed on the human body as shown in Figure 87. A user can directly see the textures and colors of the fabrics in a virtual environment. Textures and colors can be modified according to the mappings in application environments.

6.6 Summary

This part of the study is the logical development and application of fabric texture cognitive models in Chapter 3, fabric search in Chapter 4, and pattern classification in Chapter 5. Fabric texture analysis and operations converges when the object orientation database system is introduced. The importance of fabric texture operations have been maximized by putting the fabric texture in a meaningful application environment.

Fabric pattern interpolation is defined with respect to a fabric design process in which the gamut weaves of the input fabric texture have been generated and used in a phase image to obtain a new fabric pattern. The output ability of fabric pattern interpolation has been maximized by cognitive models of fabric texture analysis and operations. The effort of that includes how to use the gamut weaves of the fabric texture to create new fabric textures. Three possible ways to generate new fabric textures are proposed: weave pattern interpolation, colorway pattern interpolation and Jacquard texture interpolation. The application results in the last part of this chapter indicate that fabric search, pattern classification and interpolation could be studied in a systematic way. The research framework provides fabric texture management experience for the textile industry.

Chapter 7:

Conclusions

A digital textile database in the textiles and clothing industry usually comprises a large number of fabric texture images. An efficient tool to browse and manipulate the textures in the digital database management system is indispensible. A systematic investigation on fabric texture analysis and operations, such as search, classification, and pattern interpolation, was carried out in this study. The study finds that it is very helpful to introduce cognitive informatics models to study fabric textures and their applications. Attributes of the material units and properties of fabric textures were integrally linked as expressions of an irreducible essence. This chapter summarizes the work done in this project and describes possible directions for future work.

7.1 Fabric texture analysis

The object-attribute-relation called OAR model is introduced for fabric texture analysis in Chapter 3. As the model explains how information or knowledge is represented in long-term memory (LTM), the fabric texture properties could be modeled and described by a set of cognitive features. Firstly, fabric texture is a material-based network structure that is associated with the energy cost to produce the physical structure. An increase in energy cost corresponds to higher complexity of the network structure. Secondly, the fabric textures are characterized by their structural appearances. The structural appearance is having the spatial relation of the texture elements. Thirdly, repetition size and content richness are considered to be the cognitive features among different texture features of fabric patterns.

In the section of fabric texture analysis, a systematic review of fabric texture properties has been conducted and a three-dimensional nature of fabric material units has been proposed for fabric texture analysis. Two levels of material units have been defined: the yarn and the fiber level. The fabric texture properties are then determined by the material units. The abstract texture fingerprints of material units are the fundamental and effective way to define fabric texture properties in order to facilitate texture-based fabric search, pattern classification and interpolation.

The purpose of the development of texture fingerprints is to minimize the gap between the low-level texture features and high-level concepts of fabric properties. Dozens of fabric images were selected to illustrate the richness of fabric appearances that were real challenges for existing computer vision applications. The large diversity and number of texture examples used in this study have significantly surpassed the examples based on which previous studies have been done. Hence, a proper statistical comparison of fabric textures on a larger scale performed in this work has resulted in a more suitable and accurate searching and ranking metrics. Furthermore, the feasibility of different feature extraction methods for these fabrics has been addressed. Automatic and interactive methods of fabric fingerprints extraction were thus developed and discussed.

Fabric texture includes both colors and structure patterns. The color patterns usually are low frequency components in the image and structural patterns correspond to high frequency components. A major challenge is that it is difficult to obtain both color and structure information from a single image. A possible solution proposed in this study is that the fiber level imaging and yarn level imaging methods were both used to acquire the necessary color and texture information correctly. A complete set of color and texture features to describe fabric details were extracted from the two-level images, which was the principal features for fabric search and classification. The research work provides a general framework for fabric texture digitization and management.

7.2 Fabric texture operations

This study introduced cognitive informatics models to study fabric texture operations. The cognitive informatics model for texture operations provides an intuitive guidance to explore the application needs and research methods of fabric texture operations. Three most important fabric texture manipulation techniques were presented. They were: fabric search, weave pattern classification and texture synthesis.

Since fabric textures exhibit a large variety of appearances, it is a challenging task to search and classify them. In particular, it is difficult to find appropriate texture features to search and classify fabric patterns that could be useful for both fabric designers and manufacturers. At the outset, a set of cognitive features were used to search and classify fabric patterns according to their essential texture properties. Also, this research work presented a framework to search and classify regular and irregular weave patterns and fabric textures.

These investigations will be a significant contribution to the textile industry as they provided the guided management of fabric collections in the marketplace.

The uniqueness of the system for fabric texture operations stemmed from the fact that the texture features obtained by search and classification could be used for fabric texture synthesis to generate new fabric textures. The new fabric textures were directly used in applications. Novel methods of fabric pattern interpolation and color theme design for fabrics were detailed to illustrate the synthesis process of fabric textures. In particular, a texture interpolation method for woven fabrics with complex designs provided a very promising application value. The framework of fabric pattern interpolation showed that fabric texture analysis and operations could be combined well in an object-oriented database system. The research work provided here will be a blue print for further research of fabric texture synthesis. Because the synthesized fabric texture on computers could show fabric designs in an efficient and user-friendly way, unnecessary demands or actions on real materials could be minimized even avoided. Thus, the value of the research work was closely related to daily life and practice for energy conservation.

The necessity and important meanings of the research work are stressed as follows. Firstly, efficient fabric swatch management, such as searching and classification, is indispensible for the textiles and clothing industry. Secondly, fabric texture interpolation and synthesis can take advantage of current collections in fabric libraries to generate new fabric designs. The new designs are evaluated by mapping the textures onto objects in virtual environments. A new texture interpolation and synthesis cycle is conducted based on the feedback of the application environments. In this way the sample prototyping cost is minimized and a green manufacturing process could possibly be achieved.

7.3 Limitations and future work

Fabric texture analysis and operations involve many disciplines, including art, material science, mechanical engineering, computer vision, and machine intelligence. It is relatively challenging to put these disciplines together and see the application values clearly in the textiles and clothing industry. The present research is an initial attempt in using the novel concepts of cognitive fabric texture analysis and operations. There exists a wide scope that can be further explored by a multidisciplinary approach.

Within the present scope of research, it is not possible to include some expensive image acquisition methods and complex mathematical models or algorithms for fabric texture analysis and operations. There are two major reasons for this. Firstly, expensive imaging methods, such as laser scanning, may capture some specific details of the local texture whereas general global texture information, such as color, is very difficult to obtain. Secondly, the complex mathematical models or algorithms are usually time-consuming and the optimization and validation cost is too high to meet the application needs. There is a trade-off between the cost and application value in fabric texture analysis and operations. Similar problems may appear in future.

An important study for further work would be a large-scale experiment of texture perception and a customized feedback system design for fabric texture operations. In texture perception experiment, greater attention can be paid to investigate how to prioritize and classify fabric textures from different resolutions of the fabric images. In the large scale experiment, it is necessary to consider the effectiveness and efficiency of the fabric texture operation algorithms. In a feedback system for fabric texture operations, an investigation of user behaviors and interests will provide more profound insights that can appropriately model the cognitive process of fabric texture operations as well as the fabric pattern design process.

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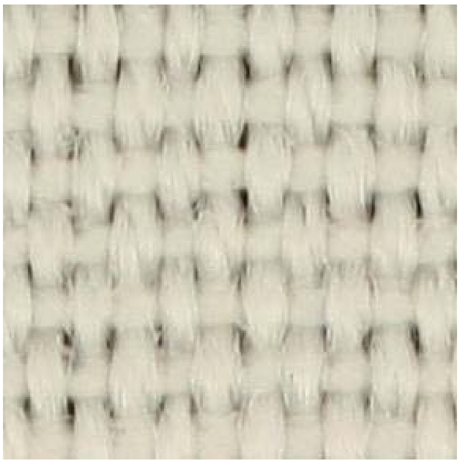
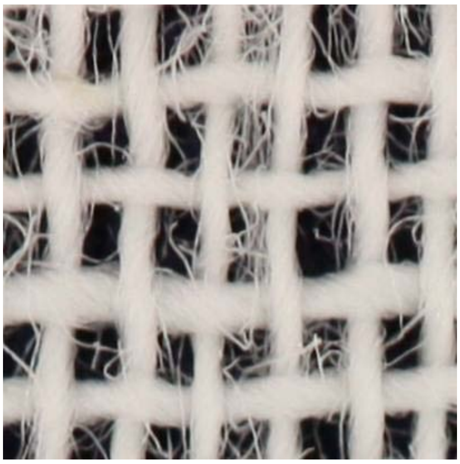
Appendix

APPENDIX A EXAMPLES OF DIFFERENT FABRIC TEXTURES

a) Solid color samples



No.1 Plain weave, high density.



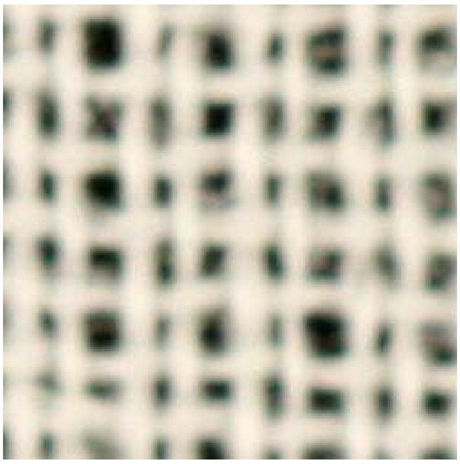
No.2 Plain weave, low density.

No.3 Plain weave, medium density.

No.4 Plain weave, clear yarn edge.

No.5 Plain weave, fuzzy yarn edge.

No.6 Plain weave, no holes between yarns.

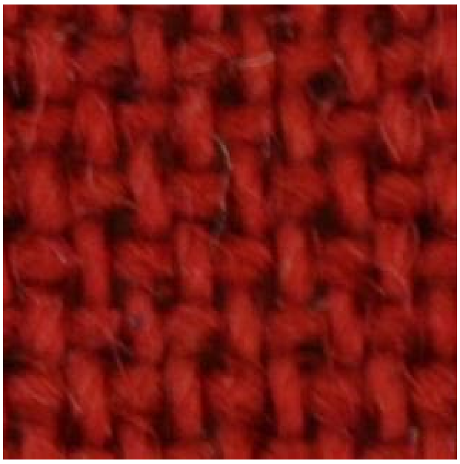


No.7 Plain weave, uneven gabs between yarns.

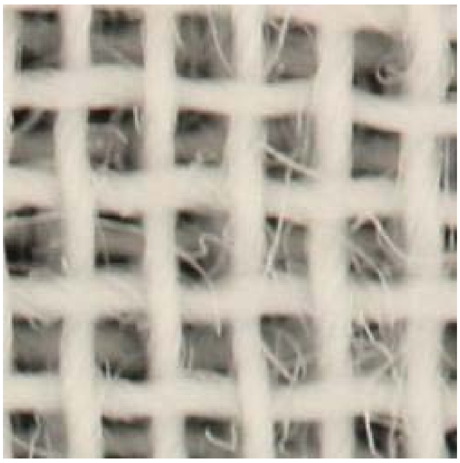
No.8 Plain weave, yarn width variation.

No.9 Plain weave, peach finishing effects.

No.10 Plain weave, dusty surface.



No.11 Plain weave, yarn distortion.



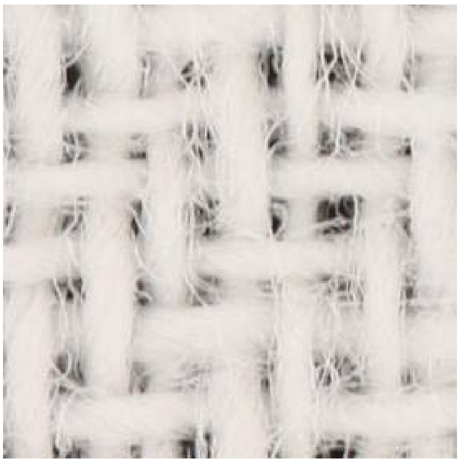
No.12 Plain weave, layered pattern.

No.13 Twill weave, 2/1pattern.

No.14 Twill weave, 2/2 pattern.

No.15 Twill weave, twisted yarn.

No.16 Twill weave, 3/1 pattern.



No.17 Twill weave, low density.

No.18 Satin weave, printed yarn.

No.19 Symmetric weave, 2/1pattern.

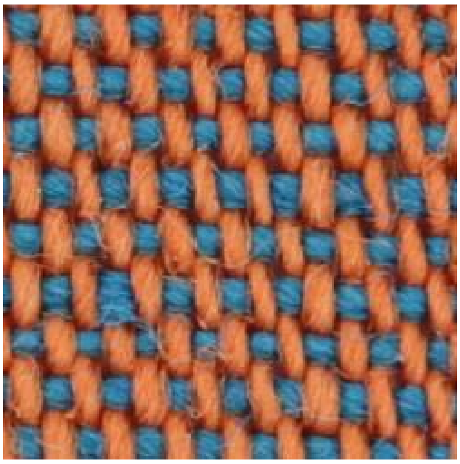
No.20 Warp rip, plain weave.

No.21 Combination weave, plain and twill.

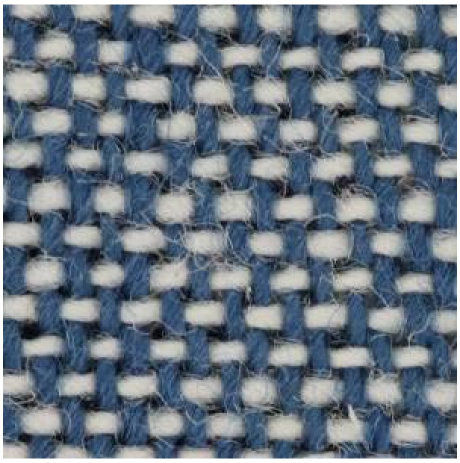
No.22 Combination weave, plain and twill.

No.23 figured weave, floral pattern.

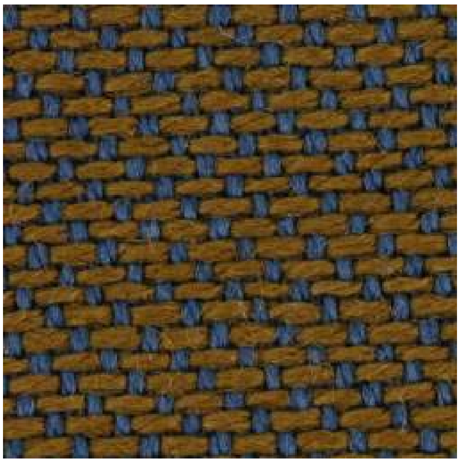
b) Dual color samples



No.24 High density, plain weave.

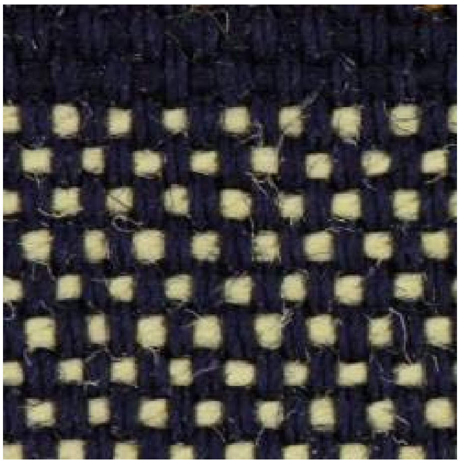


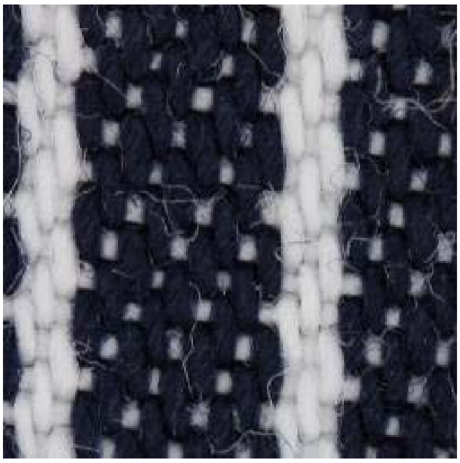
No.25 Low density, plain weave.



No.26 Weft dominance, satin weave.

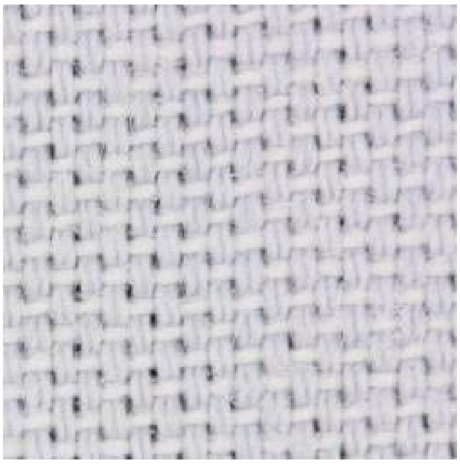
No.27 Warp dominance, satin weave.





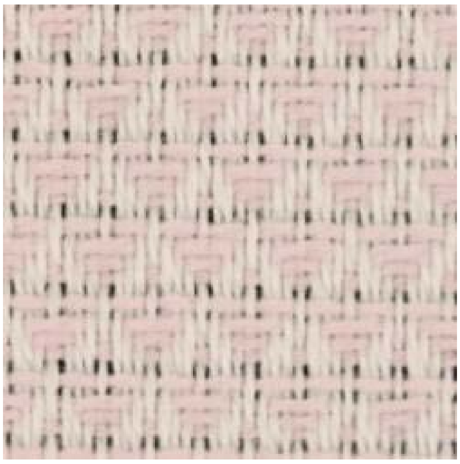
No.28 Two regions, modified plain.

No.29 Stripe regions, twill weave.



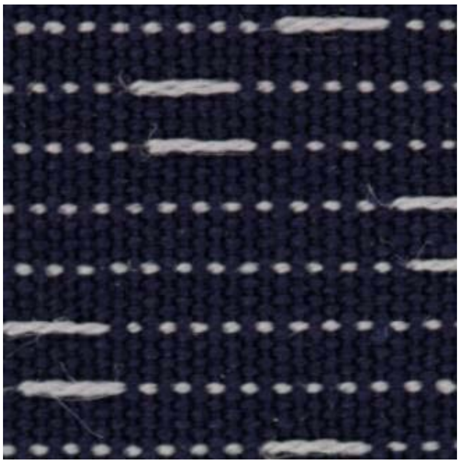
No.30 Multi regions, twill weave.

No.31 One region, double yarn.

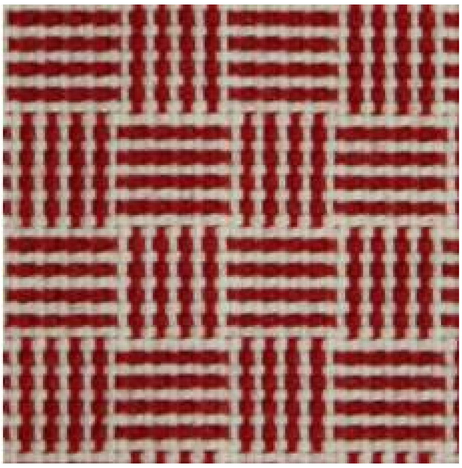


No.32 Symmetrical region, multiple weaves.

No.33 One region, symmetrical twill.



No.34 Long floats, plain weave.

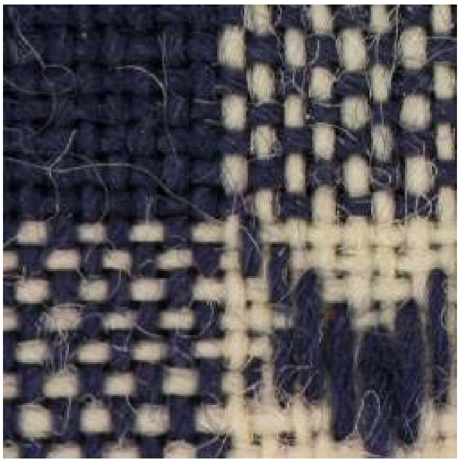


No.35 Plain effects, small stripes.

No.36 Twill floats, plain background.

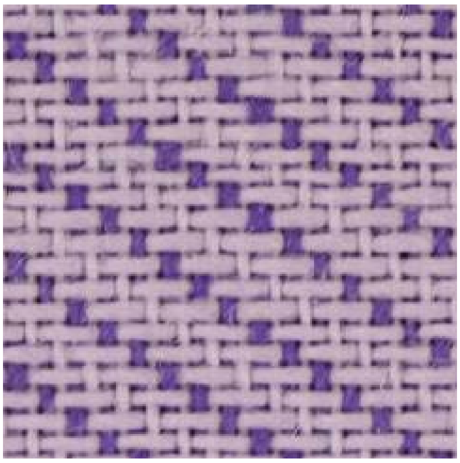
No.37 Symmetrical twill, clear yarn edges.

No.38 Two regions, weft floats.



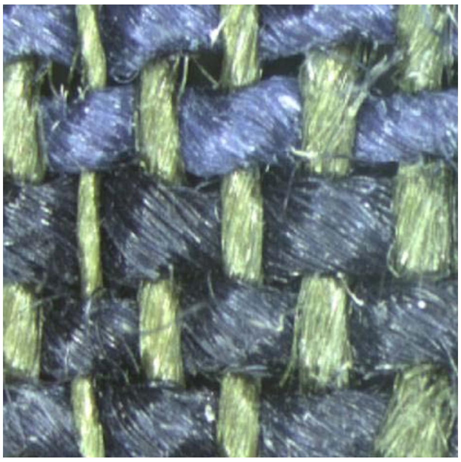
No.39 Multi regions, fuzzy surface.

No.40 Long floats, complex twill.



No. 41 Diagonal stripe, satin weave.

c) Multi- color samples

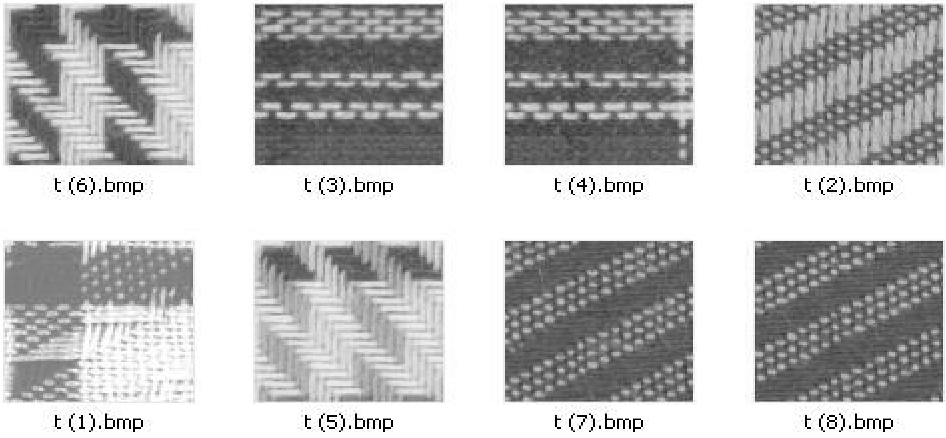


No.42 Yarn width variation, plain weave.

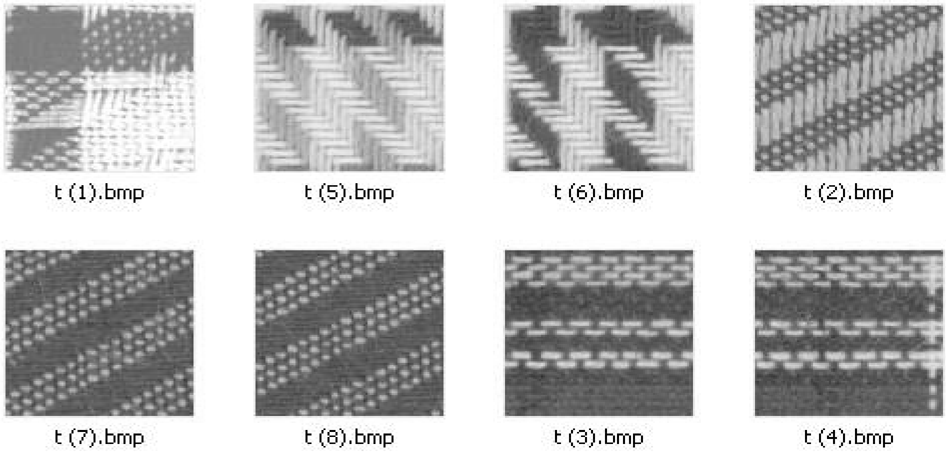
No.43 Stripe pattern, basket weave.

No.44 Multi regions, plain weave.

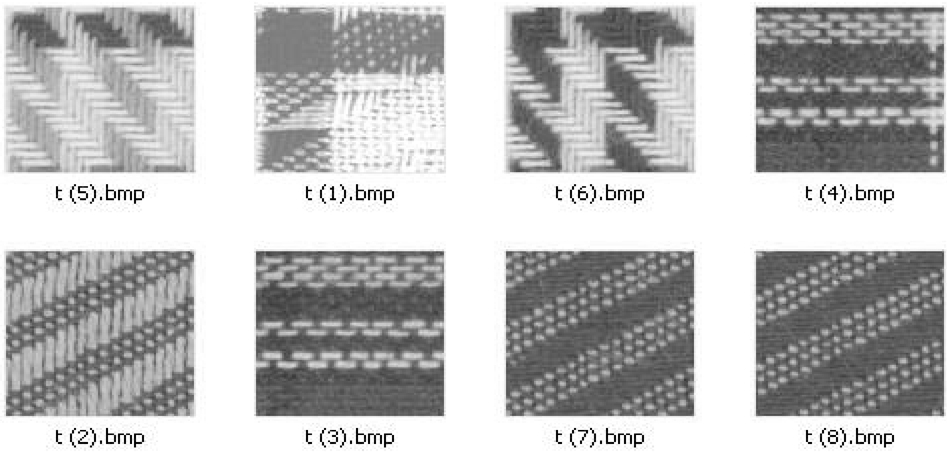
APPENDIX B FEATURE EVALUATION FOR FABRIC EXAMPLES



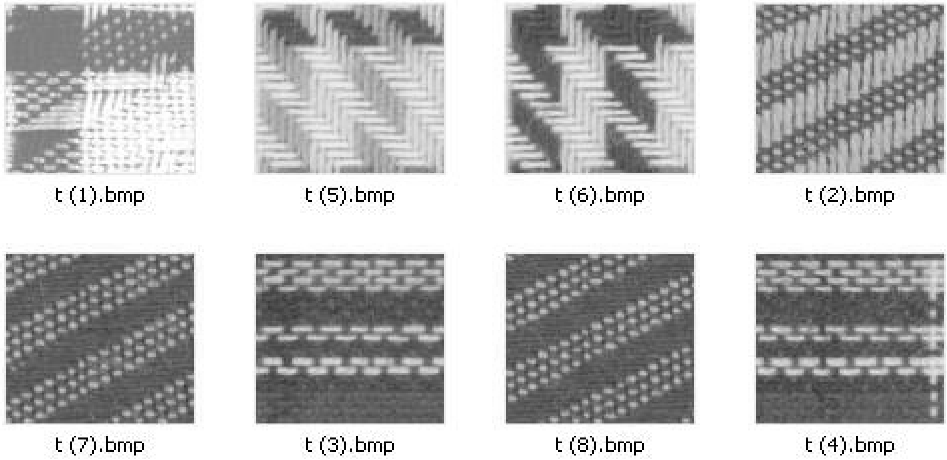
B1 Sample results by avg_value_irgl.



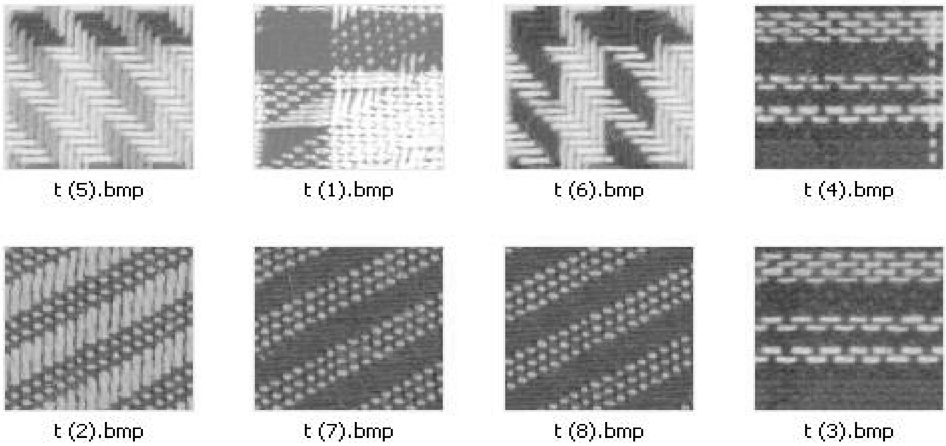
B2 Sample results by avg_value_rcgl.



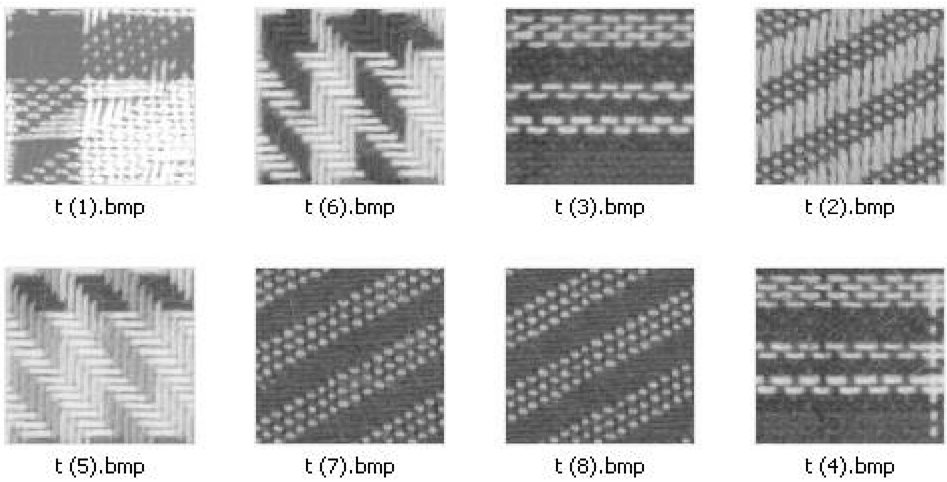
B3 Sample results by sample_mean_irgl.



B4 Sample results by sample_mean_rcgl.

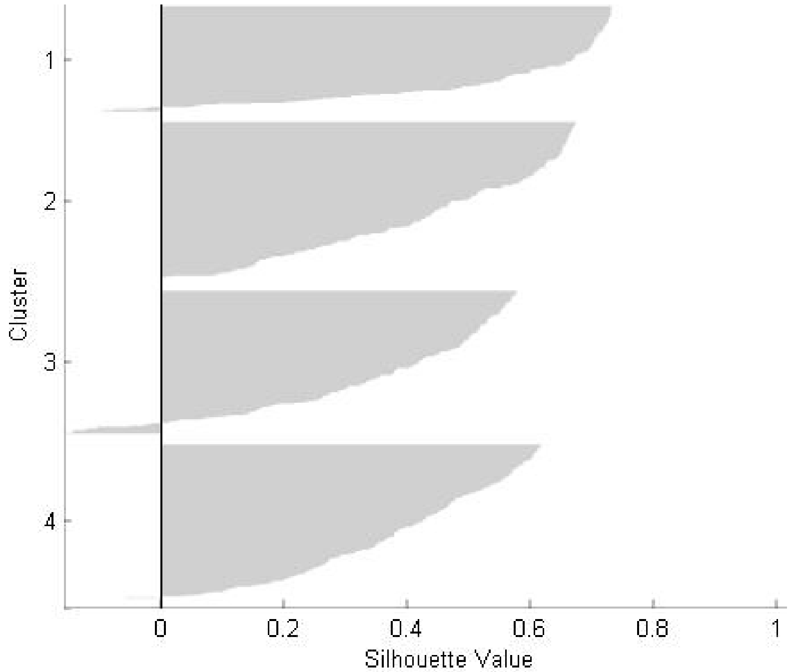


B5 Sample results by sample_SD_irgl.

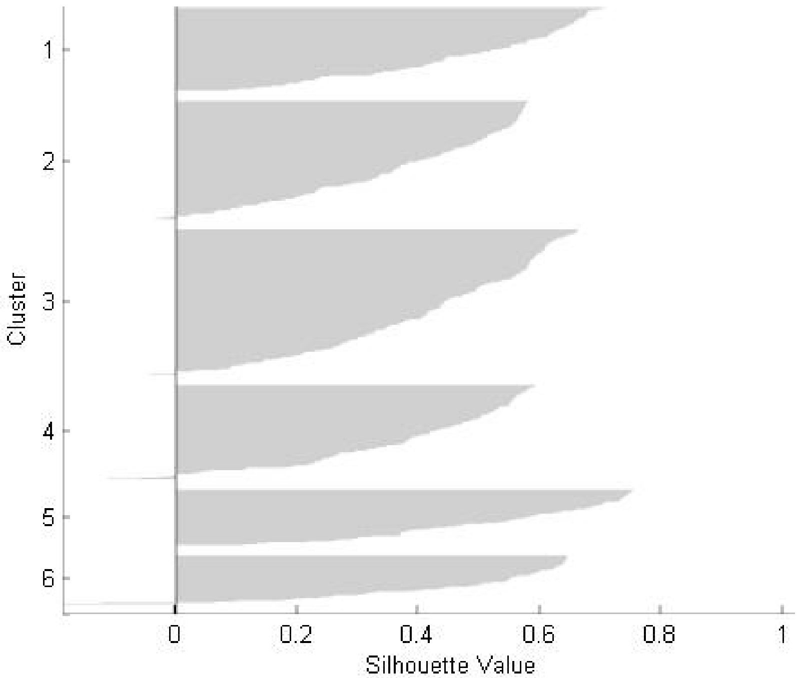


B6 Sample results by sample_SD_rcgl.

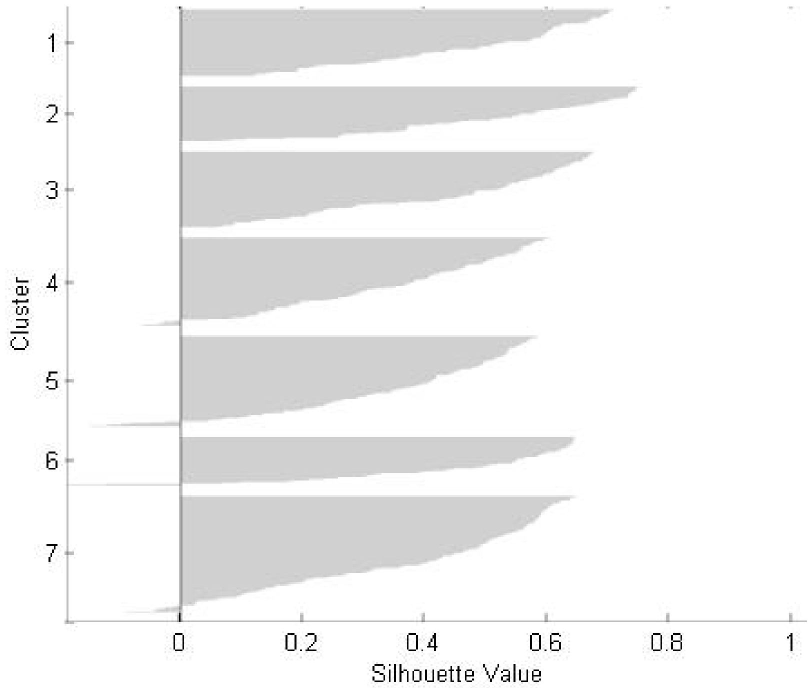
APPENDIX C CLUSTERING RESULTS WITH DIFFERENT K VALUES



C1 Clustering result (k=4).



C2 Clustering result (k=6).



C3 Clustering result (k=7).