Enhancement of Complex Network-based Texture Characterization by Spatial Texture Analysis

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Enhancement of Complex Network-based Texture Characterization by Spatial Texture Analysis

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4. Srisupang Thewsuwan and Keiichi Horio, Local Binary Pattern Mapping on Graph-based Image Representation for Texture Classification, *Proc. of International Conference on Pattern Recognition and Artificial Intelligence (ICPRAI)*, Montreal, Canada, May. 14-18, 2018, pp. 492-497.

Abstract

This thesis proposes a new texture analysis model which enhanced from traditional complex network-based model for texture characterization via spatial texture analysis. The conceptual framework of the proposed model is to synergize between pattern recognition and graph theory research areas. The results of experiment show that the proposed model can capture robust textural information under various uncontrolled environments using standard texture databases.

Texture analysis has played an important role in the last few decades. There are a growing number of techniques described in the literature, one of new area research is a complex network for texture characterization, which has developed in recent years. Inspired by the human brain system, the relation among structure texture elements on an image can be derived using the complex network model. Compared to the task of texture classification, development of the original complex network model is required in order to improve classification performance in environment variations. To fulfill this requirement, the enhancing complex network by spatial texture analysis (i.e., spatial distribution and spatial relation) has been achieved in this thesis.

The proposed approach addresses the above requirement by investigating and modifying the original complex network model by extracting more discriminative information. A new graph connectivity measurement has been devised, including local spatial pattern mapping, which is denoted as a LSPM, to encode and describe local spatial arrangement of pixels. To the best of the author's knowledge, as investigated in this thesis, the encoding spatial information which has been adapted within the original complex network model presented here were first proposed and reported by the author. The essence of this proposed graph connectivity measurement describes the spatial structure of local image texture cause it can effectively capture and detect micro-structures (e.g., edges, lines, spots) information which is critical being used to distinguish various pattern structures and invariant uncontrolled environments. Moreover, the graph-based representation has been investigated for improving the performance of texture classification. Spatial vector property has been comprised of deterministic graph modeling which decomposing the two component of the magnitude and the direction. Then, the proposed hybrid-based complex network comprises the enhancing graph-based representation, and the new graph connectivity measurement has been devised as an enhancing complex network-based model for texture characterization in this thesis.

The experiments are evaluated by using four standard texture databases include Brodatz, UIUC, KTH-TIPS, and UMD. The experimental results are presented in terms of classification rate in this thesis to demonstrate that: firstly, the proposed graph connectivity measurement (LSPM) approach achieved on-average 86.25%, 77.25%, 89.38% and 94.06% respectively based on four databases. Secondly, the proposed graph-based spatial property approach achieved on-average 90.92%, 87.92%, 96.56% and 92.65%, respectively; finally, the hybrid-based complex network model achieved on-average 88.92%, 85.46%, 95.14% and 95.52% respectively. Accordingly, this thesis has advanced the original complex network-based model for texture characterization.

Keywords: complex network, texture characterization, texture representation, texture analysis, spatial texture analysis, LBP

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Chapter 1

Introduction

Computer vision is a research field which relevant to the extraction and representation of images and videos by using computer algorithms. It comprises many problems including detection, segmentation, recognition, and classification. The focus of this thesis is the enhancement of existing complex network model for texture characterization using spatial texture analysis.

The rest of this chapter is organized as follows: The notion of texture has been introduced in Section 1.1 as well as their analysis by computer vision, including various tasks, and challenges. The motivation for this work is introduced in Section 1.2, and a problem statement of the thesis is provided in Section 1.3, including the hypotheses and the overview of the proposed approach in Section 1.4 and 1.5. Finally, the outline of the thesis and summary are described in Section 1.6, 1.7.

1.1 Texture analysis

1.1.1 What is texture?

Texture is a characteristic of physical structures and appearance assigned to an object [102]. It is an efficient way to represent the appearance of an object in an image. Texture can be defined as the visual perception of coarseness and smoothness [78]. Fig. 1.1 shows scheme idea how texture can provide an essential information for object identification based on a physical characteristic. From the application perspective, a texture is a characteristic of representing the physical properties of the surface of an

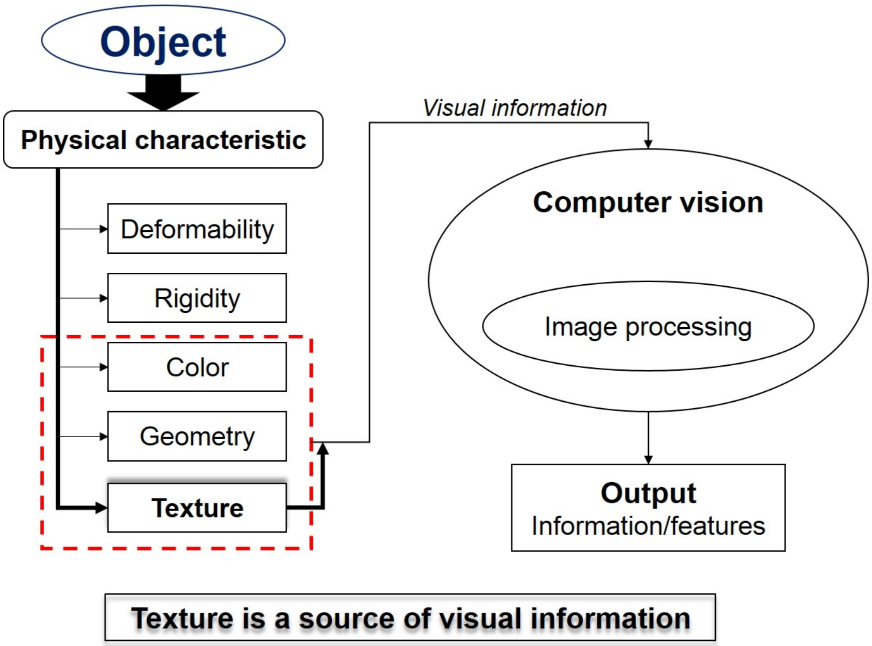


Figure 1.1: Object property by visual information.

object that is, a texture is directly related to the object's surface [1]. The notion of texture can be varied depends on the application aspects.

Texture can be arranged on a spectrum performing from regular to stochastic, connected by a smooth transition [74] as illustrated in Fig.1.2. For regular texture, these textures are similar to regular patterns. For stochastic textures, these texture images look like noise. For example, random color dots are scattered over the image which can be specified by the minimum and maximum of brightness and average color. The statistical measurement can be used to receive qualitative for the characteristic of the different textures. For instance, natural texture can provide higher entropy than artificial or human-made texture. On this hand, texture characterization is a crucial issue in computer vision and image analysis.

1.1.2 Challenges

Natural textures could be simply detected, segmented, classified and recognized by humans. We can efficiently perceive textures, for instance, we carry visual information about an observed scene through the human visual system (HVS). Nowadays, the au-

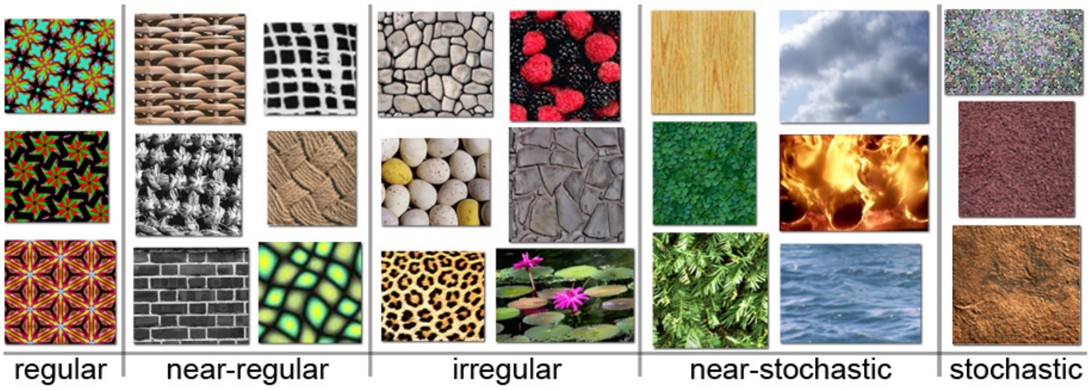


Figure 1.2: An example of texture spectrum which created by [74]

tomatic texture understanding by computer algorithm remains a challenging problem in computer vision research. Based on the conceptual idea of the level of image abstraction, they can be organized by following levels of image properties: pixel, image primitive (e.g., edge, line, curve), texture, region, object and scene. (see details explain in Section 2.1.1. For the level of abstraction in texture analysis, the texture is relatively correlated to low-level feature as compared to some object recognition and scene understanding. However, the texture is related to multiple difficulties and challenges which we will describe as below.

The primary challenge in texture analysis is the diversity and complexity of natural textures. For example, considering only plant leaves a wide range of textures can be found with different species of leaf. Their shape, color and texture as well as illumination and image acquisition variations (e.g., point of view, orientation, noise, and blur). This can be defined as a source of high intra-class variation. It is difficult for us to identify the discrimination rule among the variation. Because of selecting training samples may be significantly affected the discrimination results due to require a precise recognition models to avoid overfitting. Accordingly, developing a method to analyze various types of texture with multiple invariances is a complex task, as demonstrated by ongoing research over many decades in this field. However, the variety of definitions are given to visual textures depends on the application and type of input images.

The another challenging task is the scale of viewpoint variation on scene or object in order to recognize and classify a different texture as shown in Figure 1.3. Texture de-

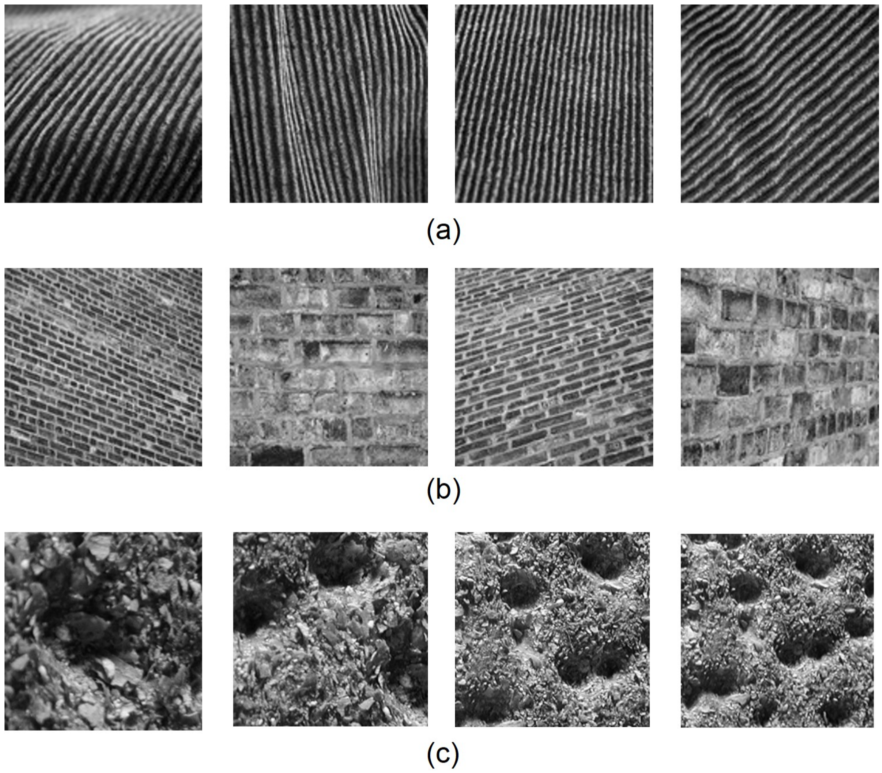


Figure 1.3: Examples of texture images from the UIUC and KTH-TIPS databases. The texture images are resulting in viewpoint changes and scale differences due to the camera angle to the surfaces.(a) Corduroy or thick cotton fabric with velvety ribs appear, (b) Bricks, and (c) Crackers on scale variation

scriptors generally require scale invariant feature while textures acquired from different viewpoints should be recognized as the same class. Moreover, in some application with fixed viewpoints, the scale can be used as a discriminative information for classification task. Multi-scale analysis is also necessary, and most applications require local and global scale invariance. In addition to the scale, natural textures may vary in terms of orientation, illumination, occlusion, and other visual appearances. Many applications require various types of invariances in order to correctly perform texture classifications. Finally, the extraction of sufficient discriminative information while maintaining moderately low dimensional and low redundancy of the texture descriptors is also a big challenge.

1.1.3 Classic approaches

The majority of texture analysis methods include feature extractions process which describe the properties of texture in order to perform recognition. Deriving features is required to extract meaningful information from a large number of pixels in an image. However, the pixels as raw data are not sufficienty descriptive, in addition to its too high dimensional data which lacks of discrimination of texture. Accordingly, various feature extraction methods have been developed in the last decades, partially inspired by the studies of human and animal visual systems [62, 67, 88].

Regarding to the literature, texture features should be informative, non-redundant and should offer robustly invariances required for a given application. Many classical texture analysis use local descriptors in the form of binary patterns [82] and filters [58] to extract local or global features. Local descriptors can be encoded into a global descriptor for an entire image or region, for instance, by a histogram of occurrence. The detail of related approaches are discussed in Chapter 2. These descriptors can be classified using machine learning methods such as Support Vector Machine (SVM). These approaches also use hand-crafted, and pre-defined local descriptors which have been outperformed by learning-based descriptors such as Bag of Features (BoF) [73] and Fisher Vector (FV) [28].

1.2 Motivation for the thesis

As mentioned in Section 1.1.3, the analysis of static textures is crucial in many applications. Most classical approaches considered hand-crafted features which lack invariances and abstraction for many applications and must be specifically designed for particular problems. Moreover, these methods do not generalize well to complex and numerous textures with high intra-class variation as confronted in various texture analysis problems. Their limitations and performance often depend on the application.

In recent years, complex network has been applied for texture analysis for modeling spatial correlation of pixels by representing pixels as a network based on graph theory [3, 16, 25, 37, 45]. Generally, digital images are represented regarding matrices, where each element corresponds to a pixel which provides a lack of representation of the original visual information in the sense that it does not consider any information about the spatial range between the pixels [37]. A graph-based approach has been applied to visual representation and analysis where each pixel is associated with a node and the difference between the visual properties of adjacent pixels are used to define respective edge weights [9]. A prototype of the complex network for texture analysis has been proposed in order to develop and investigate texture characterization for texture recognition and classification tasks since 2004 until the present. Backes et al. [16] have succeeded to develop the complete model for texture analysis. Consequently, a new area was opened for pattern recognition, where the complex network is employed as a tool for modeling and characterization of natural phenomena.

Based on the original complex network model, there are several empirical properties of image texture are discarded consideration which can be affected by the model. This model suggested that features computed from degree histograms might be able to perform texture discrimination [16]. In this stage, the model of texture has been defined as a complex network using radius r. Then, a set of threshold t must apply to the network in order to compute different network behaviors. For connectivity measurement of networks, the degree histogram is used to compute a set of desirable features. Based on this description, the radius r and the set of thresholds t are essential parameters to be configured, and it should be evaluated by concerning different configuration of these parameters.

In the complex network model, the method is performed in the spatial domain; therefore, it is based on directly modifying the value of the pixels. At this point, we can ensure that the complex network is flexible for characterizing the texture information. However, the model should be investigated and developed on, which we focus in this thesis. Our proposed approaches inspired by local binary pattern (LBP) technique [4,82]. The LBP operator is dominant feature descriptor for texture classification. The method analyzes differences between a central pixel and its neighbors by thresholding the intensities as binary numbers, also it is a great measurement of the spatial structure of local properties of image texture. Accordingly, the synergy between complex network model and LBP based on the spatial domain is a promising direction in this thesis.

1.3 Problem statements

According to how difficult in texture analysis is, modeling and describing the texture to be more functional under various environments should be investigated for the classification task. A traditional complex network model is one of a practical approach for texture representation and analysis. The model was proposed to represent the spatial relationships among structural texture elements which are a significant feature property to distinguish a different class of image.

However, there are empirical properties of image texture that are discarded which affects the capability of discrimination by the current model. For instance, if the graph-theoretical approach can characterize the structure of texture elements, the discrimination, and analysis of networks have relied on graph measurements, where can indicate the most relevant topological features. Although the degree of a node can be obtained from the topological feature result, only this feature is not enough to benefit the model robustness in accordance with various environments, such as scale difference, rotation invariance, and viewpoint variation. For an efficient texture characterization, apart from the complex network-based model concept, pattern recognition techniques should be employed for analyzing the local structure information. Moreover, if the pattern recognition technique can apply to the complex network model, how to design and integrate the model for enhancing the original complex network model-based texture analysis and classification should be further investigated.

In response to these problems, this thesis will investigate the complex network-based texture analysis for enhancing texture characterization to be more capable to capturing sufficient discriminative information. Therefore, all problems will be solved by the proposed system in this thesis.

1.4 Hypotheses

The objective of this thesis is to enhance the original complex network-based model for texture analysis and characterization, through a spatial texture analysis. Inspired by Pattern Recognition and Computer Vision concepts, in this thesis, the integrated enhancing complex network model, and invariant texture representation is devised. More specifically, the hypotheses of this thesis are three-fold:

- In order to develop a new graph connectivity measurement, the spatial distribution of pixels must be considered among dynamic network connectivity in order to capture sufficient discriminative information being used to distinguish various pattern structures. If the graph connectivity is measured by encoding the spatial arrangement of distribution of local pixels, then the spatial structure information which represents visual micro-structure (e.g., edge, line, spots) can be detected on local image texture. The encoded spatial arrangement is more invariant than using a degree of node connectivity as feature descriptors in uncontrolled environment databases.

- In order to investigate a deterministic weighted graph, the weight of edge can be developed for seeking sufficient discriminative information as texture-enriched representation. If a completed local textural information by decomposing the difference of local image difference information, i.e., the signs and the magnitude, is used for describing a topology of the graph, then the model can improve a capability of texture classification.
- The original complex network model can be enhanced with invariants in uncontrolled environment databases if integrating between the new graph connectivity measurement and the enriched graph representation is proposed.

1.5 A brief view of the proposed approaches

The proposed enhancement of complex network model via spatial texture analysis architecture consists of two aspects: pixels as network representation and network or graph connectivity measurement. Fig. 1.4 illustrates a brief view of the proposed approach in this thesis. The pixels as network representation can be generated by decomposing the multiple scale analysis and graph-based spatial properties analysis. Then, the local spatial pattern mapping (LSPM) is proposed as the new graph connectivity measurement which resulting the topology of graphs. Feature descriptors are obtained by concatenating histogram of the graph measurements with multiple-scale analysis. In order to evaluate the proposed approach, a discrimination function for texture classification was generated by the nearest neighborhood as a classifier following 10-fold cross-validation.

1.6 Outline of the thesis

In Chapter 2, the background and a comprehensive literature review are presented. The background will introduce conception of the complex network model in graph theory. The complex network-based texture analysis is introduced in this chapter. Together

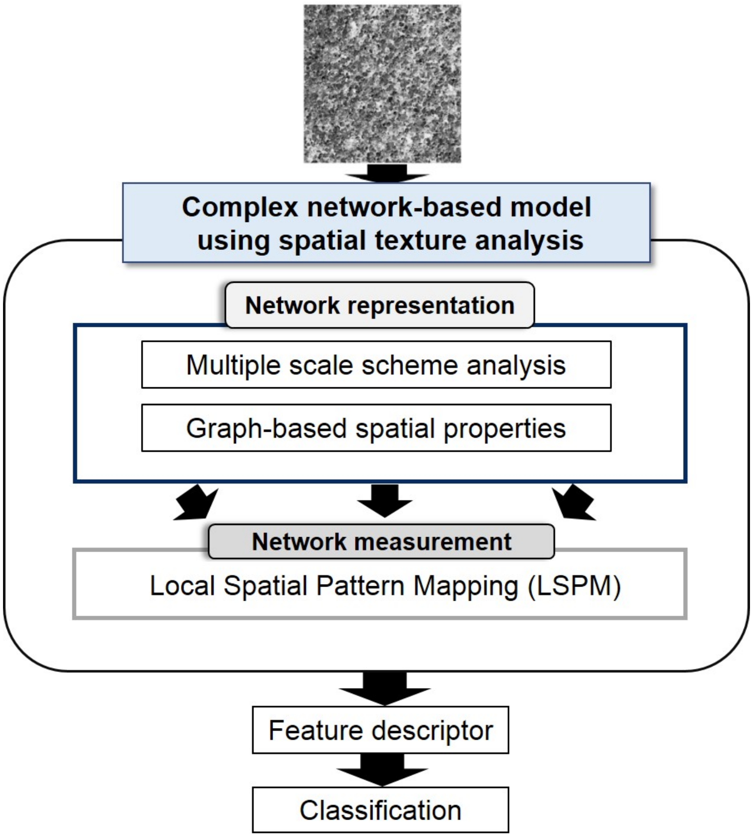


Figure 1.4: Overview of model structure.

with a comprehensive literature review of texture analysis in classical approaches and learning-based approaches. Some texture databases which is used for evaluation also discussed in this chapter. Then the achievements of this thesis are presented in following three chapters. The first aspect of achievements graph connectivity measurement will be presented in Chapter 3. The second aspect, the deterministic a graph will be detailed in Chapter 4. Chapter 5 will integrate the first and second aspects for proposing the new model. To be more specific, in Chapter 3, the local spatial pattern mapping (LSPM) will be introduced and evaluated using four standard texture databases. The experiments demonstrate that a spatial arrangement approach to capturing vital information is able to advance the degree of histogram performance. In Chapter 4, the proposed graph-based representation are investigated for enhancing the deterministic graphs in Chapter 3. The demonstrated and evaluated by using the four databases, and conventional methods are considered. Chapter 5 presents the hybrid of the proposed graph-based spatial properties (in Chapter 4) integrated into the model in Chapter 3. The experiments demonstrate that a more comprehensive and precise configuration spatial information is able to advance the classification performance. Finally, the conclusion of the whole thesis and the future work are given in Chapter 6.

1.7 Summary

This research aims to advance the original complex network-based approach for texture characterization. Texture analysis is a novel research topic and has been an attracting fast growing technique for texture characterization. This is a challenging topic and remain unclear for characterization of texture because the methods often differ on the type of images and properties. Therefore, efficient representation and invariant characterization are required. Recently, the complex network has been applied for texture analysis and classification in order to model spatial correlation of pixels which representing pixels as networks using graph theory. This proposed method is supported (underpinned) by the spatial texture analysis in which the graph theory and local binary pattern (LBP) comprising both research areas for enhancing the original in the complex network-based model. Local spatial pattern mapping can describe the topology of a graph for extracting sufficient discriminative information. Moreover, inspired by a completed local binary pattern (CLBP) approach, the magnitude and direction of weighted graphs are employed in the deterministic graph, achieving the complex network-based model for texture analysis and classification with invariant to scale, rotation, illumination when compared with the state-of-the-art.

Chapter 2

Literature Review

This chapter describes various significant approaches in texture analysis. It includes the feature extractions which describe texture information, spatial or spatiotemporal texture images in variety of applications including classification, segmentation, and other analyzes.

2.1 Texture analysis

Texture is important visual information for assessing environmental and material properties for humans. The human visual system (HVS) has regions that dedicated to processing textures which enable us to estimate object's shape or tactile perception. Furthermore, it is a basis visual property for depth estimation, motion and object recognition.

2.1.1 Human texture perception

The human perception of textures have been widely studied in the field of psychology [62] and human neuroscience [56, 59, 67] which computer vision research has inspired by human brains at a fundamental level for algorithm development. For the Human Visual System (HVS) structure as shown in Fig. 2.1[1], the human textural perception is relied on the collaboration by many different areas of the brain. At this context, the HVS transforms low-level feature in the visual input into high-level feature concepts such as scenes and object categories. We can see when visual information input at retina moves

[1] This figure reproduced from https://manumissio.wikispaces.com/Association+Visual+Cortex

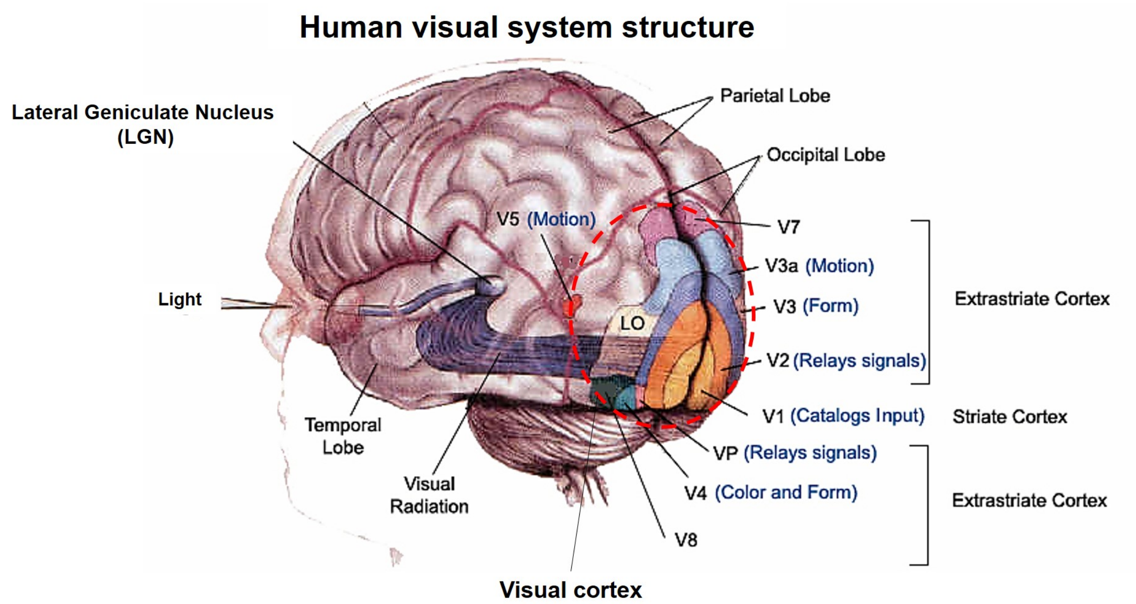


Figure 2.1: Human visual system structure

from the rear of the brain towards the anterior region, and the information is processed with increasing complexities and specificity. However, how the brain computationally represents and transforms visual features is still unclear and challenging [88].

Julesz [62] is a psychophysics researcher who conjectured that the human preattentive textural perception could not discriminate the two textures with identical second-order statistics. Then, he experimented and proposed a theory of textons which states that the elementary units of preattentive human texture perception are textons and only the first-order statistics of textons have perceptual discrimination based on similarity or dissimilarity of textons. The theory of textons has inspired and primarily influenced to the development of texture analysis including structural methods and dictionary learning-based approaches. Studied in [91], HMAX is a model that extended the idea of simple cells (for detecting oriented edges) and complex cells (for detecting oriented edges with spatial invariance) by processing in hierarchy model. The HMAX is modeled for the initial feedforward stage of object recognition in the human ventral visual pathway. In computer vision, various algorithms are used for object scene representation and spectral filtering methods such as Gabor filter banks [55, 89].

Hierarchical processing is a fundamental principle in visual neuroscience, comprising

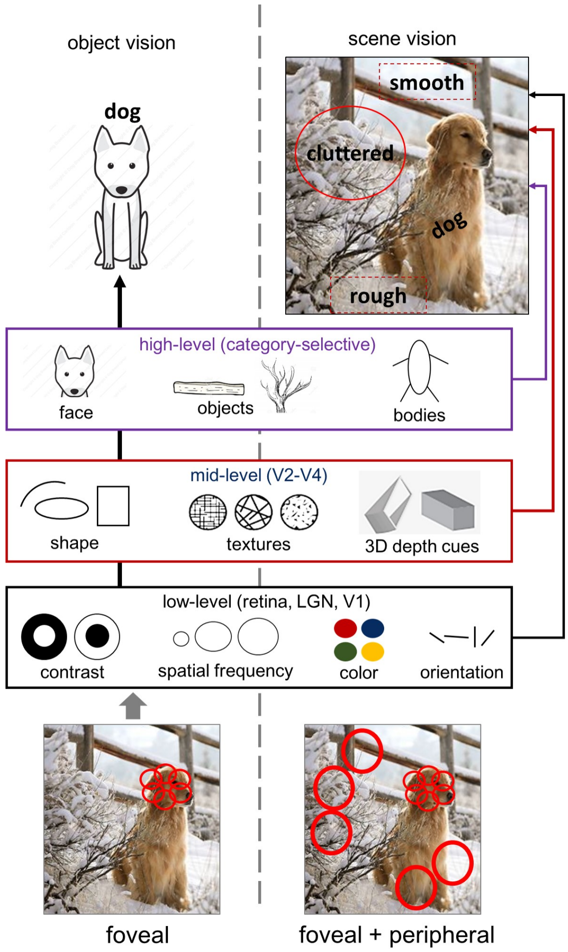


Figure 2.2: Hierarchical framework of visual perception. Figure is reproduced from [48].

a series of discrete stages with increasing sensitivity to abstract representation [56, 67]. The different stages of visual features are regularly considered in terms of low-level, mid-level and high-level representations as illustrated by the example in Fig. 2.2. Commonly, texture perception has focused on lower-level texture processing for texture segmentation and discrimination, whereas the studies of higher-level processing of visual textures have focused on judgments and interpretation of appearance and material properties related to glossiness [56, 67].

In feature extraction aspects, high-level feature relies on how we classify objects in real life and our understanding of abstract representation, whereas low-level feature mostly concerns about finding corresponding points between pixels in images, which involves the representation of elementary features, such as local color, degree of illumination and contrast in images. High-level algorithms are mostly related to the machine learning. These algorithms concern with the interpretation and classification of a scene as a whole which is inspired by hierarchical processing of the human visual system.

There are a lot of uncertainties in the field of visual neurosciences that have influenced to computer vision fields on higher-level visual representation [48, 63, 88], for instance, the amount of visual information required for each stage level representation. All of the information required to build the high-level semantic representation which are transformed from the image-based representation of Striate cortex (V1), no new information is added into but only transformed. On the other viewpoint, it might be that the information used in a high-level semantic representation is retrieved directly from low-level representation in V1 and/or earlier areas. These issues are the promising direction for researchers and are motivation to computer vision research, i.e., visual scene detection.

2.1.2 Categories of features for texture discrimination

Feature extraction in texture analysis is a crucial process to extract meaningful information from pixel values in images. After past decades with continuous research, many feature extraction methods and algorithms have emerged as described in the following sections. The majority of texture features can be found in comparative studies [72, 89, 101, 114]. There are different approaches for feature categorization grouped into statistical-based, structural-based, model-based, spectral-based, local descriptors, and learning-based approaches.

Statistical-based approaches

Statistical-based approaches can be used for describing the relationships between pixel values based on first-order, or higher-order statistics. Regarding Julesz [61, 62] who has studied texture perception for the context of texture discrimination. The statistical-based approaches can be separated into the concept of first-order and second-order spatial statistics [101]. First-order statistic is used for measuring the likelihood of individual pixel values randomly chosen in the image. For instance, the average intensity (mean), variance, skewness, and kurtosis in an image. Second-order statistics are defined by considering the distribution of observing pairs of pixel values, such as Gray-Level Co-occurrence Matrices.

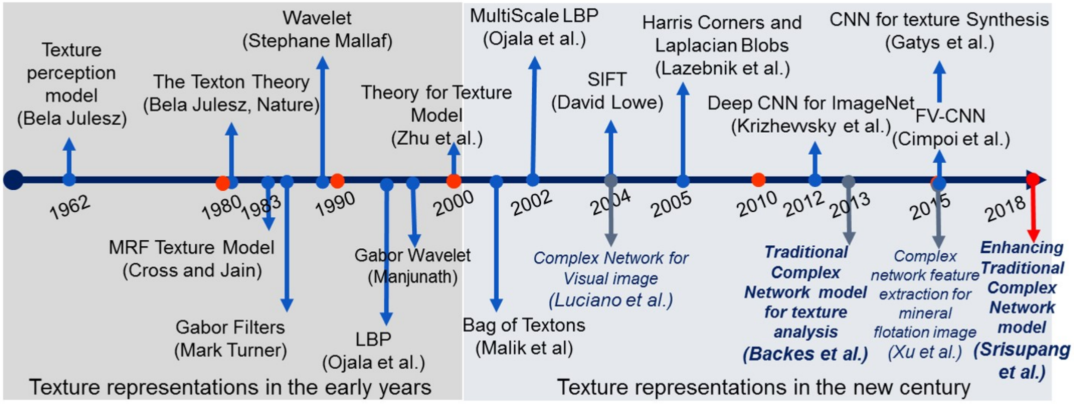


Figure 2.3: The evolution of texture representation over the past decades. Figure is reproduced from [72]

.

The GLCM [18, 19] is a 2-dimensional co-occurrence matrix which aims at describing the spatial relationship between a pixel and its neighbors by analyzing their joint probability function. Higher-order statistics analyze the joint distribution of more than two pixels, i.e., the Gray Level Run Length Matrix (GLRLM) [43]. The co-occurrence matrix-based texture features have also been primarily used in texture classification tasks and not in segmentation tasks [101]. This method requires some feature selection for selecting the most relevant features and had a variance to noise and small intensity variations.

The autocorrelation feature is one of the crucial statistical features. Texture includes the repetitive characteristic of texture element. Based on studies [107], for textures with natural repetition, the autocorrelation feature becomes more useful for evaluating the fineness or roughness, smoothness or coarseness of the texture, which can be related and detected repetitive texture patterns (primitives) and describe the regularity and coarseness of textures in the texture image.

Structural-based approaches

The structural-based approach considers textures as a composition of texture primitives (repetitive texture patterns), for example, blobs, part of regional images with uniform gray levels [101] which are arranged by the spatial organization rules or a statistical description of the primitives shapes.

Several methods have been developed to identify shape blobs using the operations of mathematical morphology [51], texture boundaries detection such as Laplacian of Gaussian (LoG) and Difference of Gaussian (DoG) filters [21,100]. As the primitives of textures are identified, the spatial relationship between the primitives can be defined as texture descriptors, furthermore, the statistics of homogeneous primitive, e.g. intensity, shape, and orientation [99]. Generally, structural approaches are mainly focused on regular textures by considering the primitives and placement rules. However, this approach does not suitable for texture with high-degree of randomness and variability of pattern, e.g. natural textures.

Model-based approaches

Several model-based approaches will be presented in this subsection. The fundamental qualities of texture in the model-based approach are captured by a model with estimated parameters. These parameters can be used as texture features or to synthesize textures of desired properties. The model-based texture analysis makes an attempt to understand a texture employing one of the following two models: generative image model (e.g. fractal features) and stochastic image model (e.g. random field features).
Firstly, we describe the generative image model by a fractal-based approach which can be used to develop discriminative and invariant features for texture classification, especially in cases where scale changes are prominent in textures [32]. In case of variations, this issue can be handled by choosing and selecting the local interest points of their characteristic scales. However, to optimize the suitable characteristic scale different textures of scale variations should also be considered [30]. Based on the literature, we found that fractal features are demonstrated as promising results which overcome scale constraint, but the results also depend on resolution of an image [108].
Secondly, the stochastic image model such as random field feature image textures can be modeled as a Markov random field (MRF) of pixels gray-level. The MRF approach describes the spatial relationship between the gray values of neighboring pixels, capturing local contextual constraints to model an image globally [65]. For example, a Gauss-Markov random field-based probabilistic texture model [31] is developed to characterize hyperspectral textures. The MRF is a graphical model which using an undirected graph corresponding to pixels as random variables with edges only between neighboring pixels. The parameters of the model are estimated by responding an image based on an optimization method that minimizes an energy function. The estimated

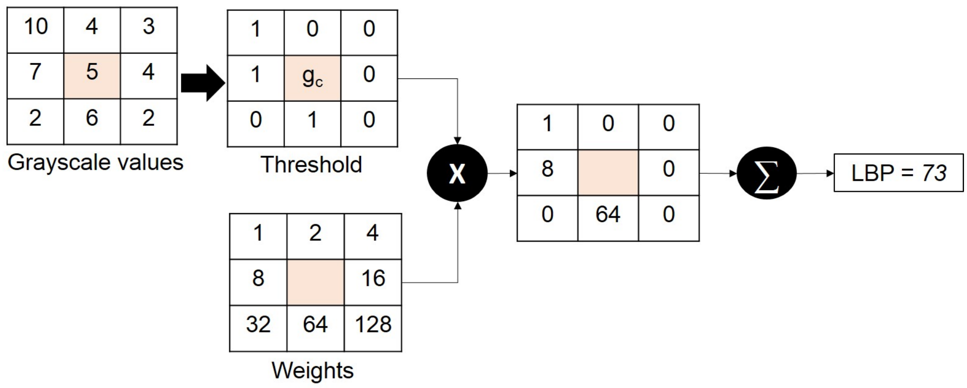


Figure 2.4: The original LBP operator calculation

parameters are regularly used as texture features. Significant difficulties with random field methods include determining an appropriate energy function and optimizing it.

Spectral-based approaches

In this sub-section, we explains spectral-based or filter-based features which mainly including Gabor filter, Fourier filter, and Wavelet filter. Results of Fourier transform-based features [11] lacks the robustness of various spatial localization of an image. Gabor filters or Wavelet filers are more extensively employed for texture analysis.

Gabor filter-based texture features are necessary features for texture analysis [55, 58,89]. Moreover, Gabor functions shares lots of relevant features similar to the human visual system (HVS) [91]. They consist of a sinusoidal plane wave of frequency and orientation, which is modulated by Gaussian envelope. The Gabor filter can be defined as a band-pass filter that useful for extracting a specific band of frequency parts from images [96]. For texture analysis, we can use a set of Gabor filters with different frequencies and orientations for feature extraction in discrimination task. For example, Linear-Gabor features, Thresholded-Gabor features, and Gabor-energy features, etc.

The multi-resolution properties of the wavelet transform are useful for classifying textures [52]. However, the wavelet transforms are usually computationally taxing. The disadvantage of the wavelet transform was computational complexity and the spatial resolution of the wavelets which discards spatial information. However, wavelet transform have flexibility to choose different functions for different applications.

Local descriptors (LBP)

The local texture descriptors aim mainly to provide local representations which invariant to illumination, contrast, rotation, scale, and probably other criteria. The local binary pattern (LBP) texture operator was first introduced as a complementary measure for local image contrast [83]. Fig. 2.4 shows an example of an LBP operator calculation. The operator works with the eight-neighbors of a pixel, using the value of the center pixel as a threshold. An LBP code for a neighborhood was produced by multiplying the thresholded values with weights given to the corresponding pixels and summing up the result. A binary code that describes the local texture pattern is built by thresholding a neighborhood by the gray value of its center. Based on Fig. 2.4, it can be explained by the following mathematical:

$$LBP_{P,R}(x_c, y_c) = \sum_{p=0}^{P-1} s(g_p - g_c)2^p. \tag{2.1}$$

where,

$$s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \tag{2.2}$$

where g_c corresponds to the gray value of the center pixel of a local neighborhood. $g_p(p = 0, \ldots, P-1)$ correspond to the gray values of P equally spaced pixels on a circle of radius $R(R > 0)$ that form a circularly symmetric set of neighbors. In the equation (2.1) the signs of differences in a neighborhood are interpreted as a P-bit binary number, resulting in 2^P distinct values for the LBP code. The LBP method can be regarded as a truly unifying approach. Instead of trying to explain texture formation on a pixel level, local patterns are formed. Thus, the LBP distribution can be used in recognizing a wide variety of texture types, to which statistical and structural methods have conventionally been applied in a wide array of fields and has demonstrated efficienct performance in several comparative studies [79, 84, 94].

LBP has been extended its development based on the original LBP operator which derived from a general definition of texture in a local neighborhood. First, [83, 87] rotation invariant texture is proposed based on local binary pattern. Rotation invariance is achieved by recognizing the gray scale invariant operator incorporating a fixed set of rotation invariant patterns. To remove the effect of rotation, a unique identifier is assigned to each rotation invariant local binary pattern, which is given by:

$$LBP^{ri}_{P,R} = minROR(LBP_{P,R}, i)|i = 0, 1, \ldots, P-1 \tag{2.3}$$

where $ROR(x,i)$ performs a circular bit-wise right shift on the P-bit number x in i times.

The next extension for improving rotation invariance with uniform patterns. [83,87] mentioned that the occurrences frequencies of the 36 individual patterns performed vary greatly. The proposed uniform circular structure that contains very few spatial transitions. The first rows of Fig.2.5 illustrated the uniform pattern. To defined the uniform pattern, [83, 87] introduced a uniformity measured by $U('binarypattern')$, which correspond to the number of spatial transitions or bit-wise changed 0 and 1 in the $'binarypattern'$. The patterns which correspond to uniformity pattern and non-uniformity pattern according to U value of at most 2. This approach can be defined by:

$$LBP_{P,R}^{riu2} = \begin{cases} \sum_{p=0}^{P-1} s(g_p - g_c)2^p & ifU(LBP_{P,R} \leq 2 \\ P+1 & otherwise \end{cases} \tag{2.4}$$

where

$$U(LBP_{P,R} = |s(g_{P-1} - g_c) - s(g_0 - g_c)| + \sum_{p=0}^{P-1} |s(g_p - g_c) - s(g_{p-1} - g_c)| \tag{2.5}$$

We noted that subscript ^{riu2} reflects the use of rotation invariant uniform patterns that have U value of at most 2. Fig.2.5 illustrated the 36 unique rotation invariant local binary pattern which represented by [83, 87]. These patterns can be considered as the LBP codes of some possible local patterns, including spots, flat areas, edges, edge ends, and curves.

In the present, the LBP has been extended its development on discriminative performance. For example, Completed LBP (CLBP) [49], Extended LBP (ELBP) [73], Dominant LBP (DLBP), Local Ternary Patterns (LTP) [95] and Median Robust Extended LBP (MRELBP) [75].

The Completed LBP (CLBP) [49] has been proposed for extracting three complementary descriptors. First, intensity component is captured from the center pixel using global thresholding. Secondly, Sign and magnitude components are defined by decomposing the local difference sign-magnitude transformation. The intensity, sign and magnitude components are encoded into a CLBP descriptor.

The Extended LBP (ELBP) [73] is extended the CLBP approach by approaching four components as texture descriptors. The first two components are based on lo-

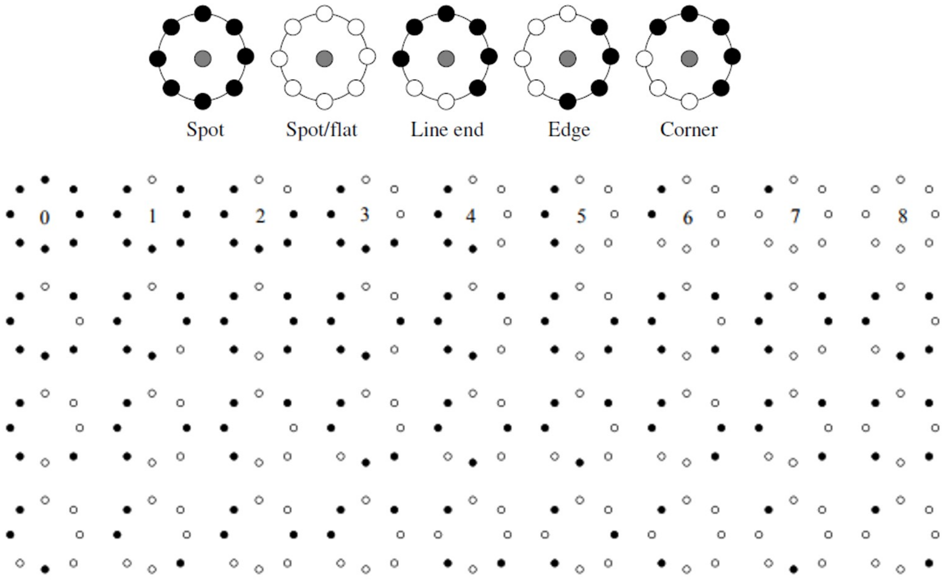


Figure 2.5: The 36 possible rotation invariant LBP^{ri}(8,R) The nine uniform LBPs (LBP^{riu2}(8,R)) are depicted in the first row. Figure reproduced from [83]. Illustration of $riu2$ which refer to rotation invariant uniform pattern.

cal intensities, of center pixels for one and neighbors for the other. The other two components are based on local differences.

For Dominant LBP (DLBP) is extended from the original LBP by using the most frequent patterns in the image to describe textural information. This approach considers complex patterns discarded by the uniform LBP in [4] which may be frequent and representative in some textures (e.g., high curvature edges, crossing boundaries or corners). The resulting DLBP descriptor is combined to Gabor-based features to capture complementary global textural information. Global rotation invariance is obtained in [6] by extracting features from the Fourier transform of the LBP histogram on the entire image.

Moreover, many extensions have also been developed to reduce the sensitivity to noise, for example, the Local Ternary Patterns (LTP) [95]. The LTP is computed using two binary patterns to maintain a relatively small dimension of the histogram which is twice as large as the LBP. Other descriptors have been extended from the LBP to build robustness to noise and blur including Median Binary Pattern (MBP), Noise Tolerant Local Binary Pattern (NTLBP), Robust Local Binary Pattern (RLBP), Noise Resistant

LBP (NRLBP) and Median Robust Extended LBP (MRELBP) [75]. These methods offer various options to encode the local differences with low sensitivity to noise while retaining a high discriminative power of the descriptors.

Learning-based approaches

In Fig. 2.3, since in the 1990s, the promising research direction of invariant feature representation was acknowledged for developing robustness variation such as illumination, scale, rotation, etc. For instance, the local invariant descriptors such as Scale Invariant Feature Transform (SIFT) [76] and LBP [82] were a milestone of invariant local features for development. Continuously, in 2012 deep Convolution Neural Networks (CNN) on ImageNet [68] achieved record-breaking on image classification accuracy. Following that, computer vision has been focused on deep learning methods for many problems, which including texture analysis [27–29]. Besides, texture is a spatial phenomenon. Texture characterization cannot be succeeded by a single pixel, and regularly requires the analysis of patterns beyond local pixel neighborhoods. Accordingly, a texture image is transformed for pooling local features, which are aggregated into a global feature for an entire image or a region. Moreover, when the texture properties are considered by translationally invariant, most texture representations or characterization are based on an order-less aggregation of local texture features, such as a sum or max operation.

A significant number of CNN-based texture representation methods have been proposed since 2012 when ImageNet classification result is announced [68]. A crucial success of CNNs is their competency of learning large labeled datasets to extract and to understand high-quality features.

Learning CNNs, however, amounts an estimated millions of parameters and a vast number of annotated images, which is a constraints when using limited and small scale training data in CNNs application.

CNN-based features pretrained on large datasets were found to achieve very well to many problems, including texture analysis with a relevance adaption effort [26, 29, 85, 90]. Together with performing finetuning for specific tasks of texture classification is also employed in the current literature. Comprehensive evaluations of the feature transfer effect of CNNs for texture classification have been conducted in [27, 29, 86], with the following critical insights. By focusing on model transfer, features are extracted from different layers which could achieve different discriminative performance. Experiments have confirmed that the fully-connected layers of the CNN tend to exhibit relatively critical generalization ability and transferability. Accordingly, the CNNS would need retraining or finetuning on the transfer target. This point can inform us that, the source training set is related to classification accuracy on different datasets, and the source and target play a critical role when using a pretrained CNN model [20]. Based on [27,29,86] works, it was found that deeper models transfer better and that the deepest convolutional descriptors give the best performance, above to the fully-connected descriptors when reasonable encoding techniques are employed (such as FVCNN features with Fisher Vector encoder) to the model.

The most straightforward approach to CNN-based texture classification is to extract the descriptor from the fully connected layers of the network [27,29] e.g., the FC6 or FC7 descriptors in AlexNet [68]. The fully connected layers are pretrained discriminatively, which can be either an advantage or disadvantage, depending on the information that can be transferred to the domain of interest [26,29,44]. The fully-connected descriptors have a global receptive field and are usually viewed as global features suitable for classification with an SVM classifier. On the other hand, the convolutional layers of a CNN can be used as filter banks to extract local features [27, 29]. Compared with the global fully-connected descriptors, lower level convolutional descriptors are more robust to image transformations such as translation and occlusion. Although, the pretrained CNN model is capable of classifying images in different objects or scene classes, it may be discarded in distinguishing the difference between different textures (material types) based on images in ImageNet which may contain different types of textures (materials).

In case of finetuning CNN models, generally, this model performs on task-specific training datasets which finetuning is supposed to improve the pretrained CNN model [26, 44]. When using a finetuned CNN model, the global image representation is usually generated in an end to end learning (all parameters are trained jointly); that is, the network can produce a final visual representation without supplementary specific encoding or pooling steps. The characteristics of the datasets which used in finetuning are also crucial to learning discriminative CNN features. The size of the dataset which used in finetuning also have significance to the model as well, cause too small datasets may be lacking for complete learning. Andrearczyk and Whelan [10] observed that finetuning a network that was pretrained on a texture-centric dataset can achieve better results when compared to a network pretrained on an object-centric dataset of the same size. Moreover, the size of the dataset which used in the network is pretrained or finetuned outstandingly influences the performance of the finetuning as well. These two observations can confirm us about an extensive texture dataset could bring a significant contribution to CNNs in texture analysis.

2.1.3 Texture analysis problems

The discriminative feature of textures can be extracted from every pixel, interest point and pooled, in term of a local descriptor into a global descriptor for a texture region or an entire image depending on the application task. Here, we should note that the concept and notation of texture may have different definition or viewpoint perspective depending on the given objective and application tasks. Texture analysis can be related to numerous areas of classification, segmentation, and synthesis. Notwithstanding, texture characterization or representation is a core of these area problems. Regarding a classical-based approach in pattern recognition problem, texture classification fundamentally consists of two significant subproblems which including texture characterization and classification [57]. Basically, it is agreed that the enrich texture feature plays a relatively significant important role, even if poor features are used in the best classifier, it will fail to achieve good results [72]. Notwithstanding the numerous decades of development, texture features have been continuously developed the performance for real-world textures. On the other hand, in many computer vision applications, the texture features development requires the real-time complexity of computation.

As Section in Learning-based approach, CNNs features have grown deeper in the quest for higher classification accuracy. Depth or deeper layer has been shown to be relevant to high discrimination ability and also interpretability increases with depth as well. Ref. [35] investigated and confirmed representations at different layers resolve different categories of meaning, and that different training techniques can have a significant effect on the interpretability of the representation learned by hidden units. Accordingly, the relation between the depth of a network and the complexity and spatial support of the features varies between architectures.

In viewpoint of feature characteristic, it is important to distinguish between the affine invariances required for general computer vision tasks (e.g., ImageNet) and some texture datasets which only require invariances to rigid motions. For instance, the CNNs trained on ImageNet learned invariance to scale which may have a negative impact on datasets such as Brodatz, forest species datasets and tissue images with fixed viewpoints and where scale can be a discriminative property. With small training sets, it might be difficult to control what CNNs learn as discriminative features. It could be deceived, for instance, by orientation, illumination, scale, and shapes which are only present in the training set as the invariance to these transformations must be learned through training. A network may learn to recognize a particular shape or object which is part of the training texture images rather than the texture of interest. On the other hand, invariance to specific variations, or knowledge of which type of feature should be inquired can be optionally required in shallow classifiers. However, designing appropriate simple hand-crafted features is more natural and may perform better in some scenarios. CNNs might also be combined with hand-crafted knowledge and features in an ensemble manner. This problem often referred to as the black box, is related to the difficulty in tracing the prediction of a network back to important features, and revealing the internal process of a model. Therefore, here as texture characterization, the inevitable difficulty in obtaining powerful texture representation is relevant to two challenging issues; high-invariant and high-expertise representation.

High-invariant related challenges of texture characterization mainly rely on how to develop the texture representations with high robustness and distinctiveness. For instance, the large intraclass of datasets which consist of appearance variations caused by changes in illumination, rotation, scale, blur, noise, occlusion, etc., and potentially small interclass appearance differences. An additional difficulty is in obtaining sufficient training data in the form of labeled examples, which are usually available only in limited amounts due to collection time or cost.

High-expertise related challenges include the potentially large number of different texture categories and their high dimensional representations, which have motivated by big data. Here, the big data is associated with the high challenges and the scalability or complexity of huge problems. Furthermore, the applications supported by a limited resources platforms such as embedded and hand-held devices, these issues have to be considered in promising research direction between highly compact and efficient texture representations.

2.2 Complex network-based descriptor

2.2.1 Complex networks

Complex network research emerges between the graph theory, physics, statistical mechanics and computer science [36], which are all active area of scientific research inspired by the real-world network such as computer networks [7, 23], brain networks and sociology [81, 106] as illustrated in Fig. 2.6. The research is mainly defining new concepts and understanding of structural properties. The main result has been used for the identification of a series of merge principles and statistical properties which familiar to most of the real networks. There are numerical review articles [8, 80] and books [2, 106] from which might be useful for the reader to consult. Therefore, it possibly opened a new promising research direction for pattern recognition, where the complex network is employed as a tool for modeling and characterization of natural phenomena.

Recently, research in the complex network has become famous in various areas such as neuroscience [92], nanotechnology [77], and various applications [39]. These can notify us about the gaining strength because of big data and recent faster computer hardware, that can enable the processing of massive amounts of data. One of the main reasons is their flexibility and generality for representing and characterizing any nature structure. Some works have examined the complex network based on the interested strcuture of network representation, followed by an analysis of the topological feature of the obtained representation performed in terms of a set of informative measurement. In the present, the direction of complex network research can be understood as the topological characterization of the studied structure. Accordingly, the obtained measurement can be used to apply in any applications in order to identify different categories of the structure, which can be related to the area of pattern recognition [33]. By quantifying topology of the complex network, we can derive its presentation which can conclude some critical information that related to the system. For instance, local vertex measures can extract essential regions of the network including its estimation of vulnerability, and groups or clusters of similar vertices, etc.

The concept of the complex network in some problem consists of two principal steps; 1) the deterministic modeling of the system and; 2) the characteristic of the resulting network which we will explain in the next subsection.

2.2.1.1 The deterministic graph of complex network model

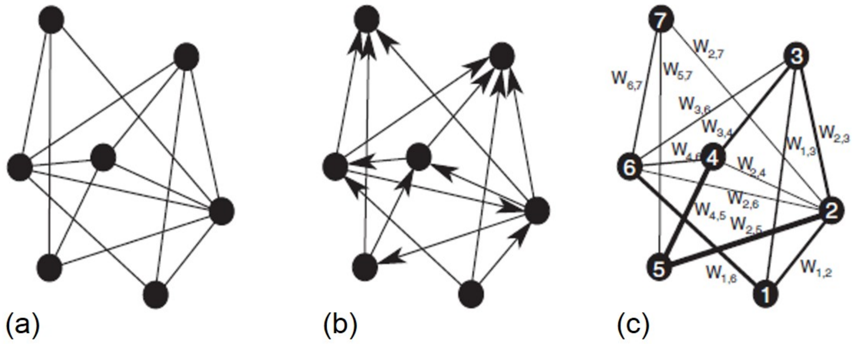


Figure 2.6: Graphical representation of a undirected (a), a directed (b), and a weighted undirected (c) graph with N = 7 nodes and K = 14 links. In the directed graph, adjacent nodes are connected by arrows, indicating the direction of each link. In the weighted graph, the values $w(i, j)$ reported on each link indicate the weights of the links, and are graphically represented by the link thicknesses [22]

Graph theory is an important framework of complex network [9, 23]. As a complex network can be represented by graph, by modeling the pairwise relation between image elements in different mathematical structure. A graph can be undirected which there is no variation between the two vertices associated with each edge. On the other hand, a graph can be directed from a vertex to another, see Fig. 2.6 for an example of graphical representation.

A undirected (directed) graph $G = (V, E)$ consists of two sets V and E, such that $V = v_1, v_2 \ldots, v_V$ and E is a set of unordered (ordered) pairs of element of V. The elements of $V_{v_1}, V_{v_2}, \ldots, V_{v_i}$ are the vertices of the graph G, whereas the elements of $E_{e_1}, E_{e_2}, \ldots, E_{e_j}$ are its edges. The number of elements in V and E are denoted by i and j repectively. A main concept in graph theory is that of reachable between two different nodes of a graph [36]. For graph structure model on images, it is useful to consider a metrical representation of a graph based on 2D images. A graph $G = (V, E)$ can be described by giving adjacency matrix A, a $V \times V$ square matrix where entry $a_{ij}(i, j = 1, \ldots, V)$ is equal to 1 when the edge e_{ij} connected to another, and zero otherwise. Several graph-theoretical approaches to image analysis and computer vision [9, 71]. They are interesting graph-based approach to visualize representation and analysis. Graphs can represent each pixel to a node, and the difference between visual properties of adjacent pixels are used to define the respective edge weights. The advantage of graph-based approaches is that several useful image properties can be derived from such graph representation.

2.2.1.2 Characteristic of the resulting complex network

The important properties of the complex network can be understood by a network measurement [36, 115]. Network measurements are essential promising direction research, including representation, characterization classification and modeling. Fig. 2.7 explains the mapping of the generic complex network into the feature vector x such as vertex degree. These mapping can provide the representation of network. Based on this strategy, the additional information can be obtained through the structure of the complex network by applying a transformation T to the original network, then obtaining the measurement from the resulting network. As Fig. 2.7, a transformation T is applied over the original network to obtain a transformed structure which extracted from the new measurement X_T. Generic mappings can be used in order to obtain the characterization of the network in terms of a suitable set of measurements. In case the mapping is invertible, we have a complete representation of the original structure. Additional measurements of a complex network can be obtained by applying a transformation T on it and obtaining a new feature vector X_T . The difference ΔX between the original and transformed features vectors can also be considered in order to obtain additional insights about the properties of the original network.

The related researchers also have been discussed for obtaining a richer feature along the growth of the network. It is possible to derive from a set of measurement along with network transformation. However, there are still significant questions of how to choose the most appropriate measurement. [36]. Usually, a set of topological measurement can be indicated by statistic approach. The available network measurement in order to select a suitable set of feature has been used. Namely, the average vertex degree, average shortest path length, and clustering coefficient were topically considered for complex network characterization. The area of this stage is still open issues and promising research direction.

The idea of this work is similar to the above related work and it focuses on pattern recognition of texture. Due to its importance to human communication, representing

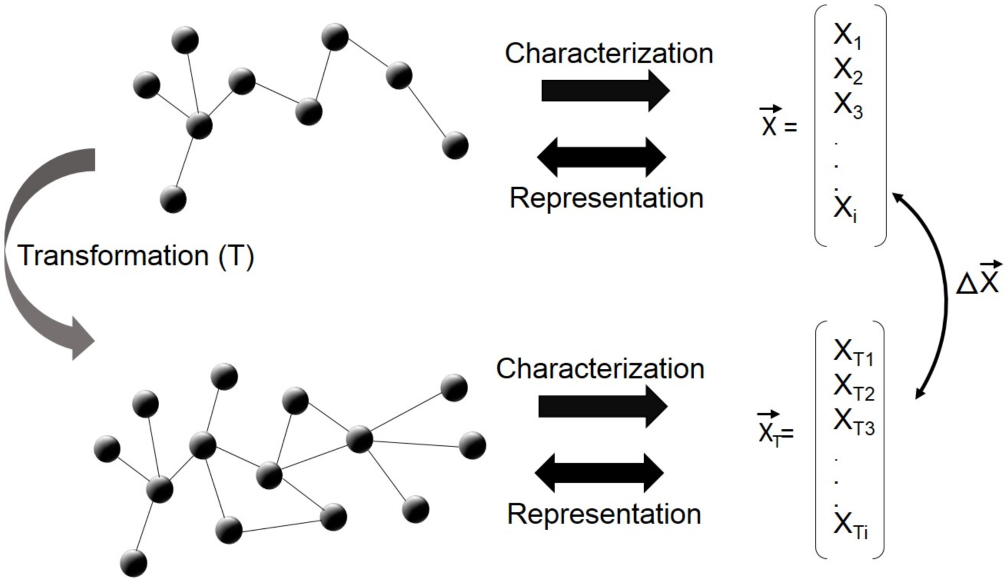


Figure 2.7: The mapping from a complex network into a feature vector

and analyzing images in terms of graphs and complex networks offers a promising research opportunity in forthcoming years.

2.2.2 Complex networks in texture analysis

A texture pattern can have many or few texture primitives (micro-textures) and/or hierarchic spatial arrangements of these primitives (macro-texture). The textural perception of an image depends on the spatial size of these primitives. Large primitives give rise to macro-texture (i.e. coarse texture) and small primitive to micro-texture (i.e. fine texture) as we explained in Section 1.1.1. Due to this characteristic, the definition of a texture class must take into account not only the isolated primitives, but also the relation among them and their neighbors. Consequently, texture characterization and identification require a methodology which is able to express the context surrounding each pixel, therefore joining local and global texture characteristics.

The complex network theory is also growing consideration from the computer vision research. From the proposal of modeling an image as a network, many possibilities arise, where the solution became a network problem. Since 2004, Luciano et al. [37,38] proposed a general framework to integrate the areas of vision research and complex

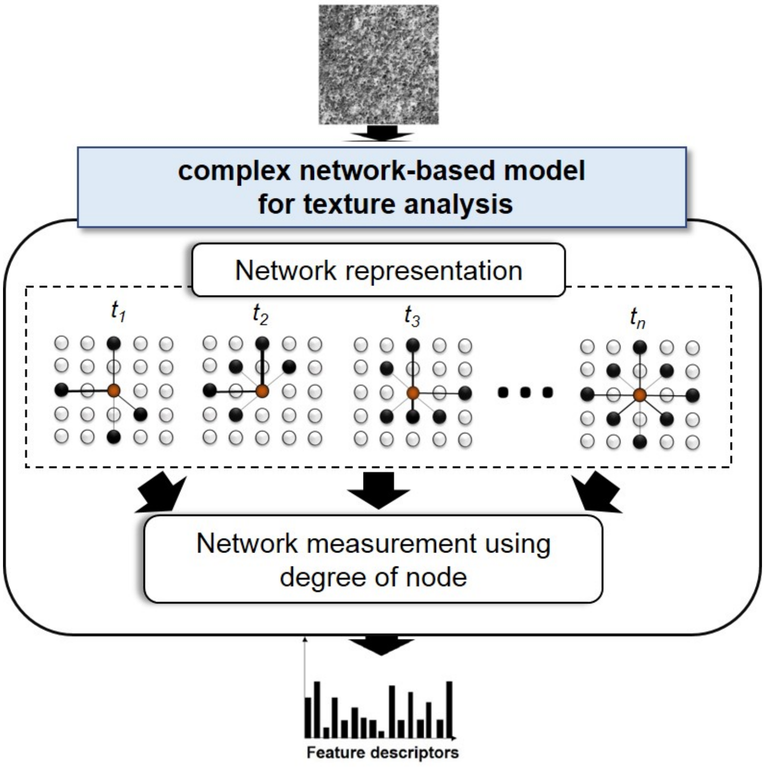


Figure 2.8: Overview of the original complex network model for texture analysis by Backes et al. [16]

network where each pixel is represented as a node and the distance between gray-level. The difference between every pair of pixels in the image and the distance between pixels can be considered into the edge weight. The connected graph results are subsequently thresholded at specified T. Based on these processes, we can consider all range of spatial interaction between image elements for integrating efficiently the relevant visual properties from low-level to high-level of abstraction. Moreover, another concepts and tools underlying the complex network research such as tourist walk [15, 17], shortest paths [42], community detection [60] modularity optimization [71], can be used to provide relevant information for image and object characterization.

Texture classification using complex network has firstly proposed by Chalumeau et al. [3]. They presented how complex network has been used for texture characterization and representation. The results of these propose were used for DNA representations. We can more clearly see that how useful of complex network is closely related to spatial

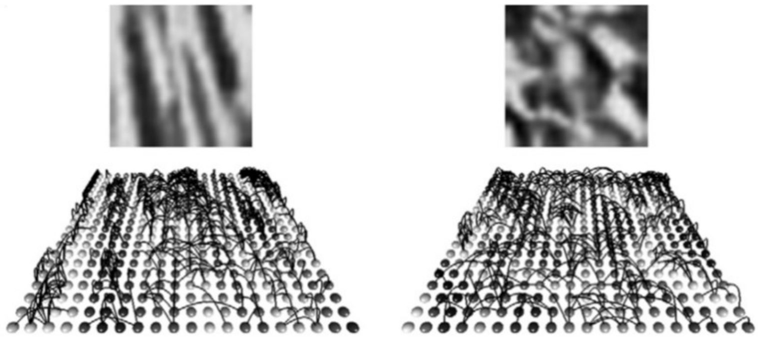


Figure 2.9: Example of two complex networks on texture images. The differences in their topological features results in measurement which can be used as texture descriptors.

correlation when appling the complex network model to characterize image textures. More related work can be shown on [25]. Texture research based on the complex network was focused in recently. Graph-based representation and complex network model have been efficiently applied in texture analysis [16, 45–47]. The idea begins to model images as networks by representing each pixel as a vertex [3,37]. Pairs of vertices are connected and considered into edge-weight by their difference in intensity. These connections can be transformed with addressing 2 parameters, a radius r for limiting spatial distance and a threshold for connection weight pooling, where high-weighted connections are removed as illustrated in Fig. 2.8. On this case, the Euclidean distance between vertices is considered as the connection weight, and the complex networks are obtained by thresholding for keeping connections between vertex and neighborhood.

Backes et al. [16] proposed an original complex network model for texture analysis and classification as shown in Fig. 2.8. Graph-based representations have been used to characterize the topological structure of networks, including of image pixels [23]. The definition of the edge of weight was introduced by using spatial information for texture analysis, and a set of different thresholds is used for evaluating the dynamic evolution of the network. In [47], the original complex network approach is extended for dynamic texture (videos) modeling by connecting vertices or pixels from different frames. The network characterization is made by vertex measures with considering connections in the same frame or between subsequent frames, providing spatial and temporal analysis. In the most recent work [45], the authors explore the concept of diffusion and random walks on the complex network modeled from texture images.

Network measurement is obtained in terms of the distribution vertex degree or number of edges incident on a particular vertex. This numerical measure of connectivity between a vertex and its neighbors can be used to characterize the texture attributes of an image. The coarseness and orientation of an image structure can be described in terms of the topological properties of the network. While most of the previous works on texture research based on complex network have focused on the characterization of the topological properties, but the spatial aspect has received less attention. Moreover, other empirical properties of image texture such as spatial arrangement are discarded from the statistical properties by the conventional vertex measurement. Fig. 2.10 illustrate an image pixel as a network which proposed by Backes et al. [16]. A graph $G = (V, E)$ denote a weight graph generated by an image. V is the vertex set and $E \in V$ is the edge set. First, each pixel of an image is a vertex in the graph. The networks are constrained by the Euclidean distance. Two vertices are connected if the distance between them no longer than radius r. The difference between pairwise pixels value can define the weight of edge. Threshold t generates the transformation of network. The degree of nodes or vertices is derived to be the network statistical properties. Fig. 2.9 shows an example of the two complex network of texture images which proposed by Backes [16]. Therefore, the differences in their resulting measurement of topological features can be used as texture descriptors in order to analysis and classification [22].

Measurement of the complex network suppose to be the edge connecting node i and j. The characterization of the topological and connectivity properties of the complex network can be achieved by using measurements borrowed from graph theory. Based on the specific topology features on the connectivity is characterized. Accordingly, the discrimination and analysis of networks rely on the use of measurements that can indicate the most relevant topological features. In the most case of complex network-based texture analysis, the related measurement is a degree of node measurement. The degree is an important characteristic of a vertex which makes deriving many measurements for the network possible by defining the number of its direct connections to other nodes.

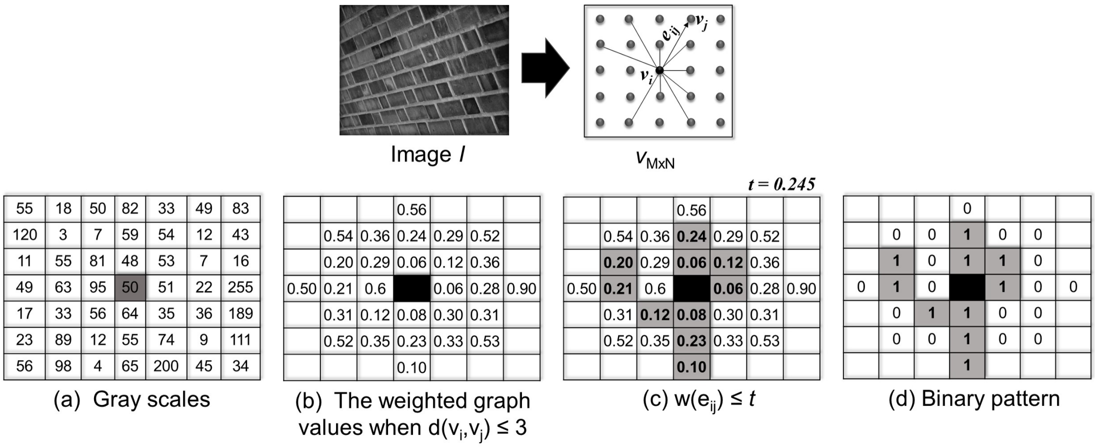


Figure 2.10: Image pixel representation based on graph theory; (a) each pixel of the image is a vertex in the graph; (b) two vertices are connected if $d(v_i, v_j) \leq r$ (r = 3) in this example), whereas a weighted graph is defined by equation (1); (c) A threshold t is applied to imitate a transformation in the network.(t = 0.245 in this example); and (d) The binary pattern transformation after passed thresholding.

2.3 Texture databases

To select candidate databases, the texture of materials are the main criteria focused in this thesis which shall only consists of grayscale texture images. Regularly, natural texture images, real-life materials, cover natural textures, and scenes are contained in selected databases. Databases contain material images under challenging conditions such as uncontrolled illumination, viewpoint variation and scale changed. Four standard texture databases which selected to evaluate proposed system are Brodatz texture database, UIUC, KTH-TIPS, and UMD.

2.3.1 Brodatz texture database

The Brodatz Texture Database or album is the most famous and the most widely used dataset in the texture analysis [66, 70, 93]. The Brodatz texture database is derived from the Brodatz album [24]. The Brodatz textures consist of the most commonly used texture data set, especially in the computer vision and signal processing community. Because they are so commonly used by previous texture analysis and synthesis works.

Databases	Resolution	Classes	Image properties
Brodatz	512x512	112 classes	Yes, varied illuminations as photos are taken in different time and places
UIUC	640x480	25 classes, 40 images per class	Yes with View-point change, Scale different
KTH-TIPS	200x200	10 classes, 81 images per class	Yes with 9 different scales, 3 in-plane orientations
UMD	1280x900	25 classes, 40 images per class	Yes with view-point change, Scale different

Figure 2.11: Various properties of texture databases

This database has 112 classes, and a small number of examples for each class. The Brodatz album contains 112 images with size 512 $\times$ 512 and 256 gray values after digitizing, showing a variety of textures, both small and large grained and make this dataset has a rich diversity of textures. Some of these textures are almost similar, yet some others are very inconsistent, inhomogeneous or non-identical. Therefore, a human may even fail to classify these in groups correctly. Overall, it is a challenging dataset to analyze [70]. Therefore, this database becomes a benchmark dataset for analyzing any new approach or model for texture analysis.

2.3.2 UIUC database

The UIUC database [70, 113] contains 40 images each of 25 different texture classes, hence total 1000 un-calibrated, unregistered images. These are gray-scale images having image resolution 640 $\times$ 480 pixels. The database includes surfaces whose texture is due mainly to variations (e.g. wood and marble), 3D shape (e.g. gravel and fur), as well as a mixture of both (e.g. carpet and brick) [70]. Moreover, within each class, viewpoint changes and scale differences are strongly evident as shown in Fig. 2.14. Uncontrolled illumination conditions are also found for this database [34, 70]. The database contains materials imaged under significant viewpoint variations and also contains fabrics which display folds and have non-rigid surface deformations [104]. Fig. 2.13 shows some images for 25 classes. The dataset has relatively few sample images per class but with

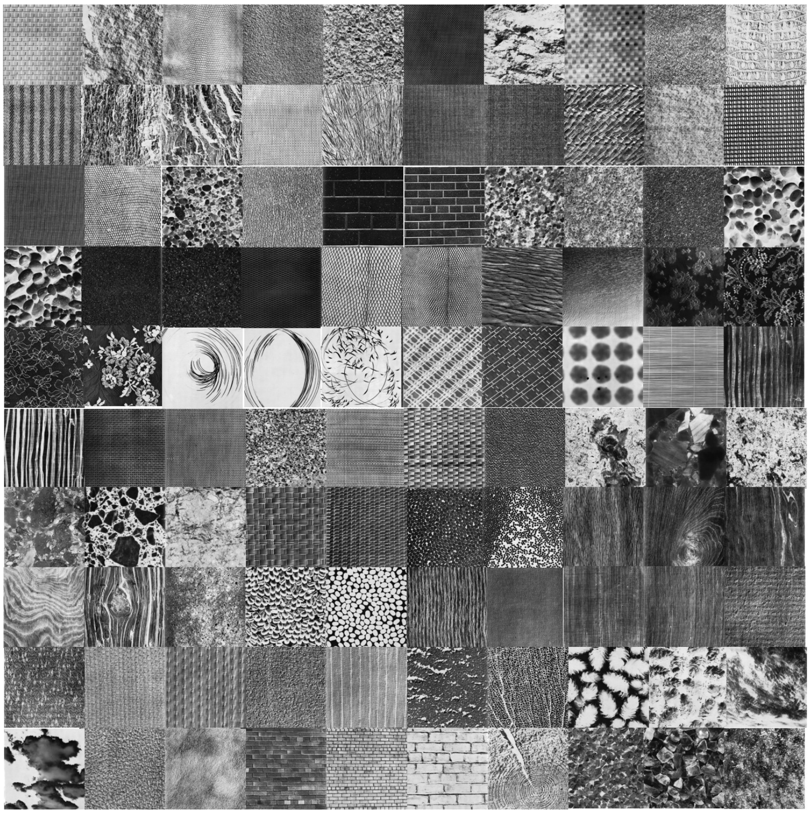


Figure 2.12: Images of Brodatz texture database.

high intra-class variability, including non-homogeneous textures and unconstrained non-rigid deformations [70]. In terms of intra-class variations in appearance, this is the most challenging one of the commonly used testbeds for texture classification [34]. Apart from this shortcoming, the UIUC database has very few instances of a given material so that it is difficult to perform categorization or to figure out generalization properties of features [103]. In terms of scale and other viewpoint variations, the UIUC database is by far the most challenging database [103].

2.3.3 KTH-TIPS database

The KTH-TIPS (Textures under varying Illumination, Pose and Scale) database expands CUReT database [40, 105] by photographing new samples of ten of the CUReT textures at a subset of the different viewing and lighting angles used in CUReT, also together with over a range of scales. Each class contains 81 images. Texture samples

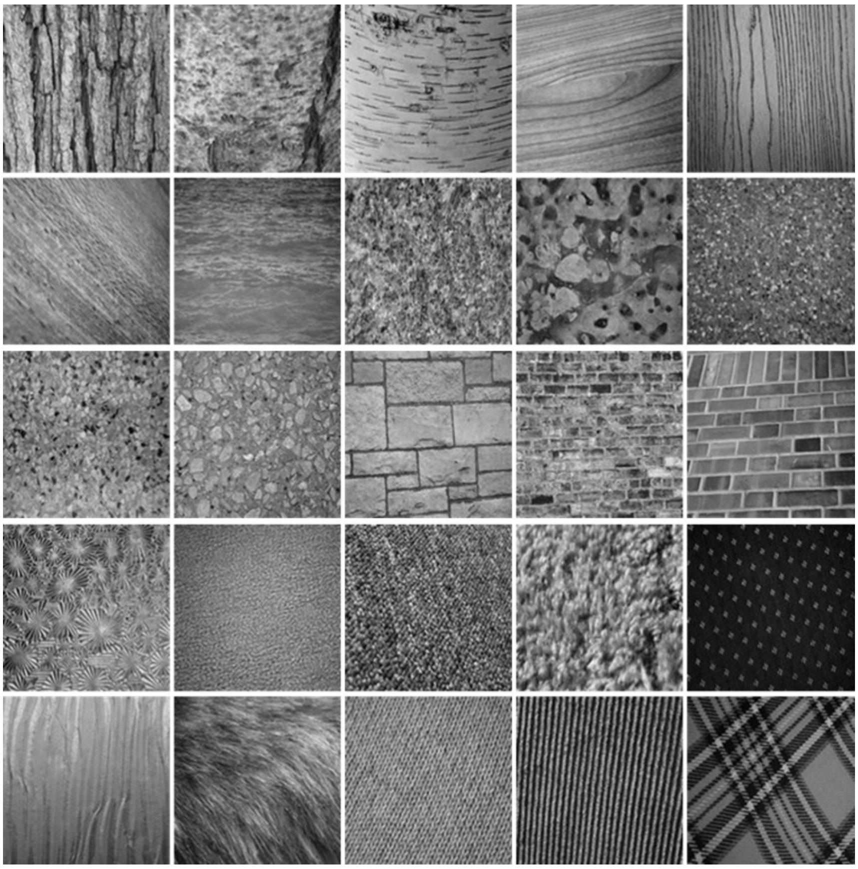


Figure 2.13: Images of UIUC texture database.

are 200 × 200 images as illustrated in Fig 2.15. Images of the materials present in the KTH-TIPS database are sandpaper, crumpled aluminum foil, Styrofoam, sponge, corduroy, linen, cotton, brown bread, orange peel and cracker B. These images are imaged at nine distances from the camera to give equidistant log-scales over two octaves [53]. At every direction, images are captured using 3 directions of illumination (i.e., front, side and top) and 3 poses, which provides a total of 9 images per scale, and 81 images per material [53]. Fig. 2.16 shows some example frames of KTH-TIPS database.

2.3.4 UMD database

The UMD (University of Maryland, College Park) is a database of high-resolution texture [109–111]that consists of 1000 un-calibrated, unregistered images, taken from a family camera. It has 25 texture classes with 40 samples, having resolution of 1280 ×

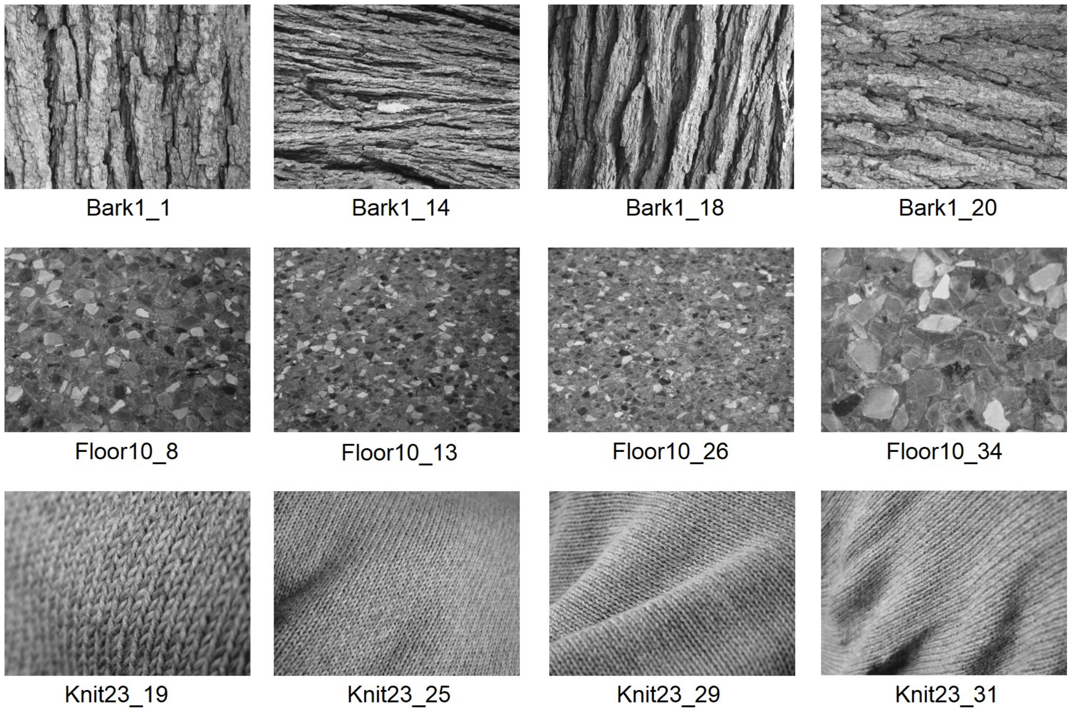


Figure 2.14: Some example images of UIUC texture database.

900 pixels as shown in Fig. 2.17. Similar to the UIUC database [70, 113], within each class the UMD texture database has significant viewpoint changes and scale differences. Moreover, the illumination conditions are uncontrolled for the UMD database. The textures of this database are non-traditional, including images of fruits, various plants, floor textures, shelves of bottles and buckets [111]. The database. Fig. 2.18 shows a sample texture image per class of UMD texture database.

2.4 Discussions

This section summarizes the limitation of the traditional complex network-based texture analysis and how to advance it. In Section 2.4.1, the limitation of the traditional complex network-based texture analysis is illustrated from two aspects: limitation in deterministic the modeling of the system and characteristic of the resulting network. Then, these limitations are summarized in Section 2.4.2, and how this thesis overcomes these limitations is introduced in Section 2.4.3.

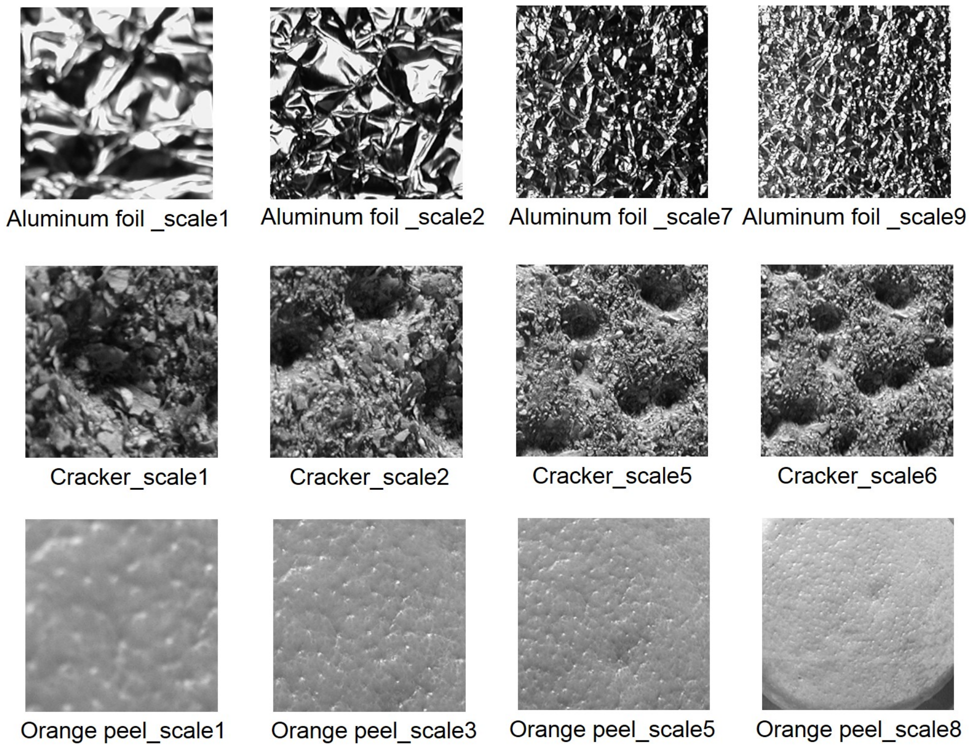


Figure 2.15: Some example images of KTH-TIPS texture database.

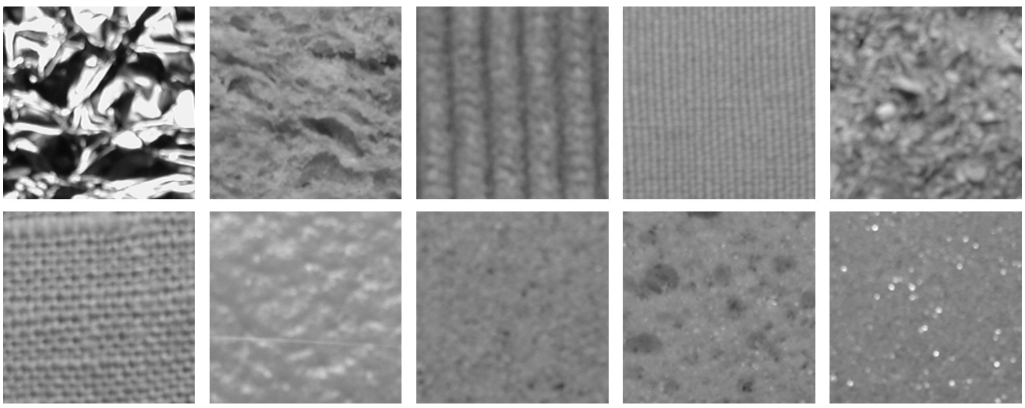


Figure 2.16: Images of KTH-TIPS texture database.

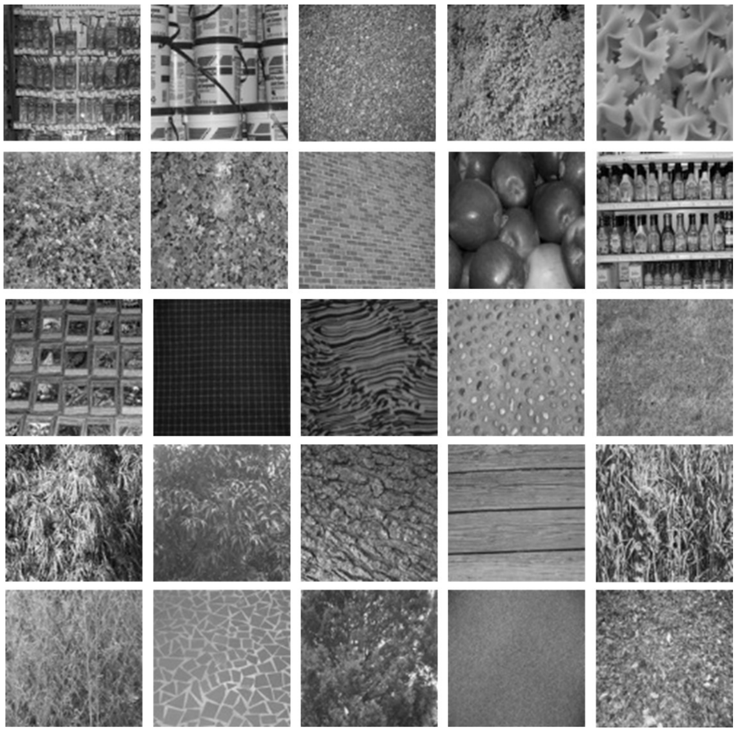


Figure 2.17: Image of UMD texture database.

2.4.1 The limitation of the original complex network-based for texture analysis

2.4.1.1 Limitation in the deterministic modeling of the system

From the investigated reported in Section 2.2, graph theory is main approach for representing pixel as network in complex network-based texture analysis. Although, graph is idea for characterizing spatial relation among a pixel and its neighbors, the deterministic of weighted graph is still lacked visual information for the tasks of texture classification. To the best of author's knowledge, Backes et al. [16] proposed a complex network texture descriptor (CNTD) that denoted pixels as a network from the difference between pairwise pixel value, which is one of the original idea for generating the weight of edges. Nevertheless, their approach faces main limitations: Firstly, their proposed approach simply defines weights of graph by using only magnitude value rather than value components. Secondly, multiple scale analysis has not been provided with respect to investigate more discriminative information.

Figure 2.18: Some example images of UMD texture database.

2.4.1.2 Limitation in the characteristic of the resulting network

The characteristic of the resulting network is important for complex network-based texture analysis because the resulting network of topological features can be used as texture descriptors in order to perform classification task. The above survey shares the common ground in terms of the network measurement: they are constrained to lack of spatial texture pattern for the discrimination capability of the model. Moreover, to generate robust texture descriptor, the model has not been provided concerning robustness to more challenging environments, such as scale different, viewpoint variation and rotation invariant.

2.4.2 Summary

Regarding the above mentioned points, the conclusion can be given that the current traditional complex network-based texture analysis usually focuses on how to manipulate the concept of the graph and the network of texture analysis tasks rather than investigating and developing the new position of texture analysis and classification research. The key limitations of the traditional texture analysis based complex network can be summarized as follows:

- The parameter radius r is a fixed rate to express the context the surrounding of each pixel rather than applying multiple scale for increasing information; therefore local texture characterization depends on the radius value.
- Existing approaches for the deterministic weight of edge are constructed based on the difference of local pixel values, which is not enough for the discrimination capability of the model when environmentally is uncontrolled.
- The traditional complex network model has demonstrated the spatial relation among structural elements of texture patterns by complex network, but the spatial structure information which is visual micro-structure (e.g., edge, line, spots) are not sufficiently investigated.

2.4.3 How to overcome

Corresponding to these limitation, this thesis provides the following solution to conquer the traditional complex network model for texture analysis:

- This thesis proposes an enhancing complex network-based model for texture via spatial texture analysis which is invariant to uncontrolled environments.
- In this thesis, the deterministic of graph is investigated for seeking more local discriminative information. Instead of using only simple local difference of pixel values, this thesis proposes a completed local textural information by decomposing the local image difference, i.e., the signs and the magnitude, for generating a topology of the graph.
- Instead of using a statistic method for graph connectivity measurement to distinguish a different class of image, this thesis proposes a new approach: encoding spatial arrangement approach for describing the context the surrounding of a vertex in network, adapted into the traditional complex network model which lead to substantial improvements on the discrimination performance.

Chapter 3

Complex Network Model and Spatial Information

3.1 Introduction

In recent years, graph-based representation and complex network model have been efficiently applied in texture analysis [3, 16, 25, 37, 45] as described in section 2.1.3. According to Backes et al. [16] who original proposed complex network model for texture analysis and classification, graph-based representations have been used to characterize the topological structure of networks, including of image pixels [80]. Network measurement is obtained from analysis of distribution of vertex degree or number of edges incident on a particular vertex. This numerical measurement of connectivity between a vertex and its neighbors can be used to characterize the texture attributes of an image. The coarseness and orientation of an image structure can be described regarding the topological properties of the network. However, other empirical properties of image texture such as spatial arrangement are discarded from the statistical properties by the conventional network measurement.

Based on the flexibility of complex networks for characterizing textural structures, it is inspirational to apply standard pattern recognition techniques to complex network model of [16] to enhance texture descriptors. Accordingly, the network or graph measurement has been investigated in this chapter. We proposed an approach to characterize texture primitives by considering spatial information based on the complex network model of Backes et al. [16] for texture classification. A multi-scale analysis is

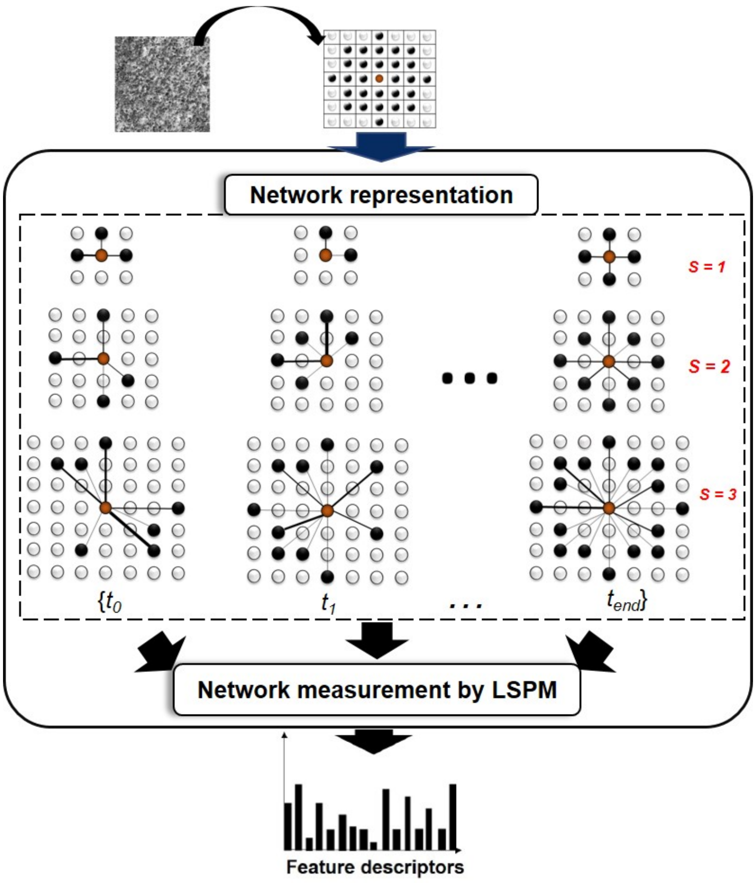


Figure 3.1: The overview of proposed structure model.

applied for extracting more and better textural information. The overview model is illustrated in Fig. 3.1.

This chapter has following main contributions summarized below:

1. A new graph connectivity measurement, denoted as Local Spatial Pattern Mapping (LSPM), is developed with enhanced performance to extract, and classify texture features in complex network-based texture characterization [98];

2. Local texture features obtained are evaluated and compared with conventional texture analysis;

3. Material images under challenging conditions, such as uncontrolled illumination, viewpoint variation and scale changed, are gathered for creating a database which

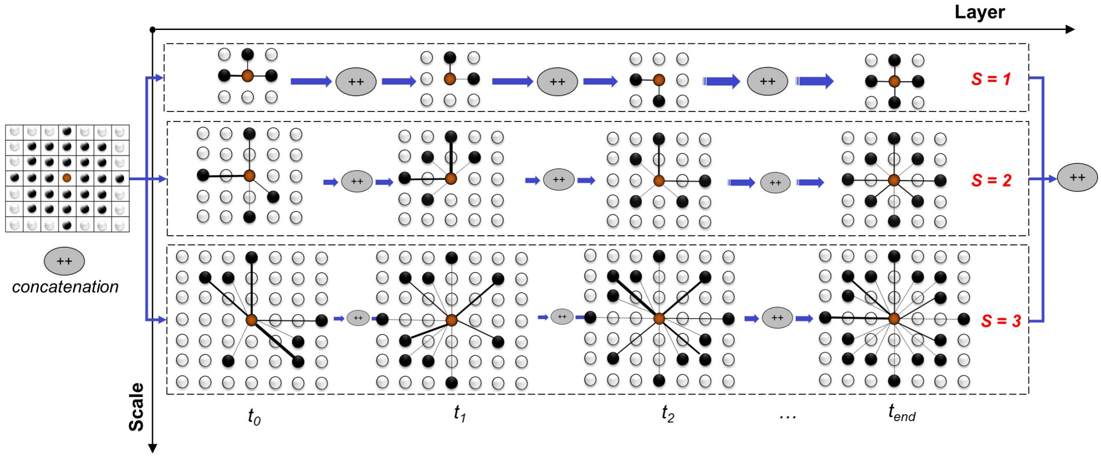


Figure 3.2: An example of the topology of graphs with multiple scales analysis and dynamic connectivity by a set of threshold.

is for evaluating the performance of the proposed model.

The rest of this chapter is organized as follows: The architecture of the proposed complex network model is introduced in Section 3.2. Section 3.3 describes the local spatial pattern mapping and its combination with the complex network model. The experiments and texture databases are presented in Section 3.4. Finally, results and discussion in our proposed model are detailed in Section 3.5.

3.2 Network graph characteristics

3.2.1 Weight of edges

The weight of edges is a parameter which represents pairwise connections between a node and their neighbors. This parameter can be used for representing a local data structure which has some numerical values. The simple local data structure of an image is pixel information which including color value and coordination. Difference of pixel intensities defines the weight of graph i.e. Co-occurrence pixels of a difference of intensity can be used for constructing the weight of edges, and consequently this approach can characterize the local image textures. For each non-directed edge $e \in E$, a weight $W(e)$ is associated, which is defined by the difference of intensity between a pixel $I(i, j)$ and its neighbors when $d(v_{ij}, v_{i'j'}) \leq r$. The weight of edges is given by:

$$W(e) = \begin{cases} |I(i,j) - I(i^{'},j^{'})| & \text{if } d(v_{ij}, v_{i'j'}) \leq r \\ 0 & \text{otherwise ,} \end{cases} \tag{3.1}$$

In this work, the weighted graph, equation 3.1, is transformed into a binary pattern for deriving context information about index pixel surroundings. This approach enables us to analyze a local texture analysis. This transformation and graph properties are discussed in the following subsections.

3.2.2 Multiple scale analysis

The radial distance pattern mapping is generated for increasing scale of the pixel connectivity as presented in Fig. 3.3. The radial graph can expand into other vertices based on the spatially radial distance measurement for multi-scale feature extraction. Fig. 3.3, each pixel of an image $I(i,j)$ is denoted by a vertex (v_{ij}) in the graph. Two vertices are connected when Euclidean distance $d(v_{ij}, v_{i'j'}) \leq r_{max}$. In this work, we have set r_{max} = 1, 2 and 3 for generating the three pattern as Fig. 3.3(the bottom). These patterns have different considering neighborhood or mapping dimensions which equal to 4, 8 and 16, respectively. Equation 3.2 can define the multiple scale analysis.

$$e = (v_{ij}, v_{i'j'}) \in I \times I \| \begin{cases} \sqrt{(i-j')^2 + (i-j')^2} \leq r_1\} \\ r_1 < \sqrt{(i-j')^2 + (i-j')^2} \leq r_2\} \\ r_2 < \sqrt{(i-j')^2 + (i-j')^2} \leq r_3\} \\ \vdots \\ r_{max-1} < \sqrt{(i-j')^2 + (i-j')^2} \leq r_{max}\}. \end{cases} \tag{3.2}$$

In Fig. 3.3, the v_{ij} and $v_{i'j'}$ represent vertices corresponding to pixel p_i and p_j, and $W(e)$ is weight of an edge. Based on radial distance mapping, we can generate a radial graph into three patterns which based on their Euclidean distance, specifically, in term of radial distance r_{max} = 1, 2 and 3 as defined in equation 3.2. Then, image-based graph representation can be represented by Fig. 3.3 (in the last row). The local pixels that have Euclidean distance $d(v_{ij}, v_{i'j'}) \leq r_{max}$ where r_{max} = 1, 2 and 3 are indicated by gray color as shown in Fig. 3.3.

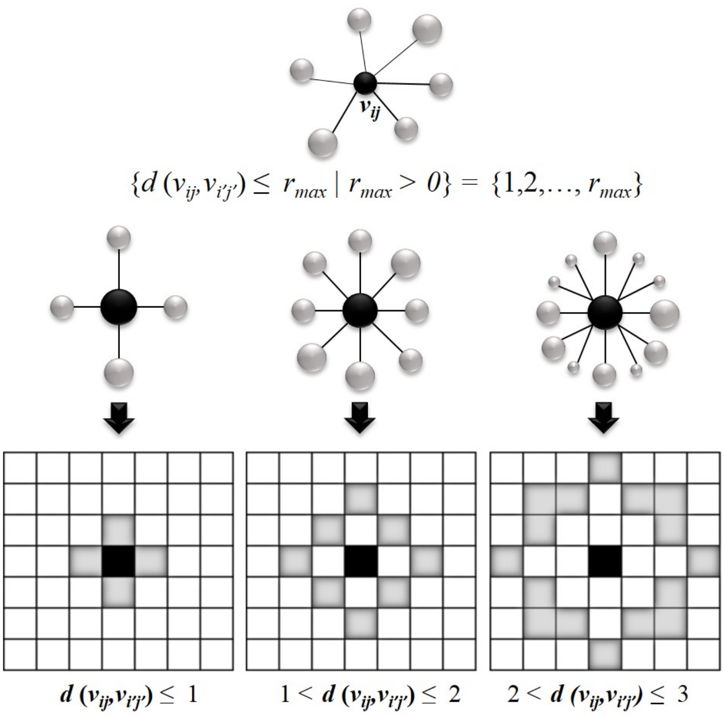


Figure 3.3: An example of pixel-based radial distance mapping based on graph representation.

3.2.3 Dynamic network transformation by a set of threshold

In order to receive additional information about the topological graph, a transformation of a graph are obtained by applying a set of threshold into the edge weight. A threshold (t) is a parameter related to the property of being an edge in graph theory [36, 80]. In the original complex network model [16], a set of thresholds is used to construct a network that imitates dynamic transformation for the purpose of texture analysis, connection weight pooling, where high-weighted connections are removed. Thus the spatial relations of the attributes of features can be determined when applying threshold parameters in the complex network model. The threshold t value is applied to the original set of edges, as illustrated in Fig. 3.2. In this study, threshold values obtained through an experiment. Then, the binary pattern transformation process is performed by converting the vertices whose weights are less than or equal to threshold t to 1, while the remaining vertices are converted to 0. This process is defined as follows:

$$W_b^{(t)}(e) = \begin{cases} 1 & \text{if } W(e) \leq t \\ 0 & \text{otherwise ,} \end{cases} \tag{3.3}$$

where t varies from t_0 to t_{end}, and experiments define the initial and final thresholds. Fig. 3.4–3.5 are shown examples of feature appearances on images when applied dynamic transformation by $t = 15$, 30 and 45 along with difference r_{max}.

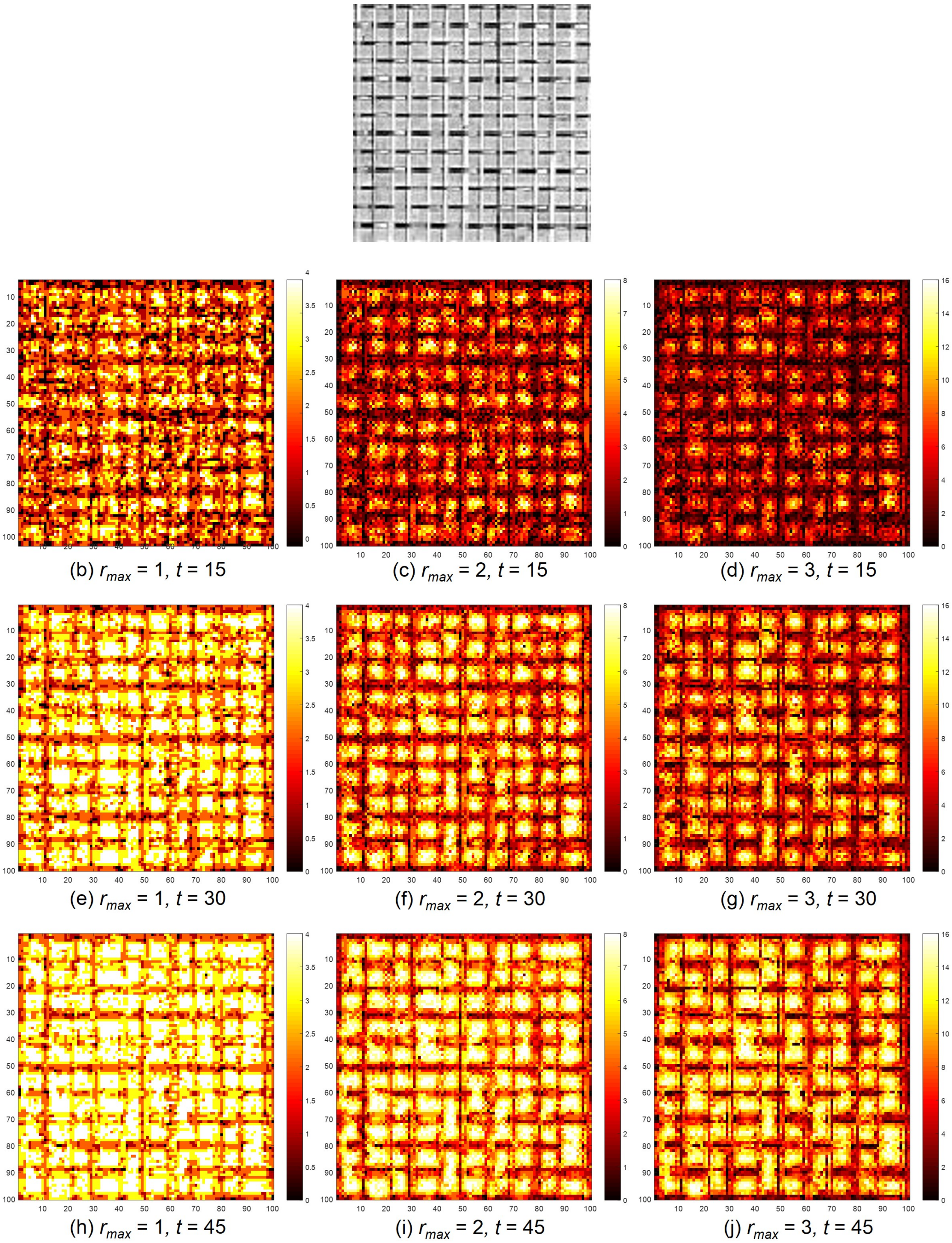
3.3 Spatial texture analysis via graph connectivity measurements

In the original complex network model [16], the texture properties are characterized by the distribution of vertex degree. However, some essential informative properties such as spatial arrangement should be determined among the extracted topological features. To our knowledge, spatial texture analysis was never previously been analyzed in texture analysis based on a complex network model. Therefore, spatial arrangement is our focus of this work.

3.3.1 Local Spatial Pattern Mapping

Local spatial pattern mapping, LSPM, is proposed to encode spatial texture pattern. As we abovementioned, $I(p_i) \in [0, 255]$ to each pixel $p_i = (x_{p_i}, y_{p_i}) \in I$ where x_{p_i} and y_{p_i} define respectively the x and y position of pixel p_i in the image. The two vertices v_i and v_j are connected, if the Euclidean distance between their pixel p_i and p_j is equal or less than a given radius r. After the binary pattern transformation, the neighbors of a vertex v_i which have Euclidean radial distance r_{m1}, r_{m2} and r_{m3} equal to 1, 2, and 3 are constructed by the radial symmetric neighborhood as in Fig. 3.3. This approach enables us to describe local context information about pixel surroundings, (indicated in gray in the figure). The results of these binary neighbors sets are used for encoding the spatial arrangement in the next process. A set of binary neighbors for a radial distance r is denoted by

$$\mathrm{k}^{(t)}(e_{v_i,v_j}) = \begin{cases} [W_b^{(t)}(e_{v_i,v_1}), W_b^{(t)}(e_{v_i,v_2}), \ldots, W_b^{(t)}(e_{v_i,v_{n_1}})] & \text{if} \quad d(v_i, v_j) < r_{m1} \\ [W_b^{(t)}(e_{v_i,v_1}), W_b^{(t)}(e_{v_i,v_2}), \ldots, W_b^{(t)}(e_{v_i,v_{n_2}})] & \text{if} \quad r_{m1} \leq d(v_i, v_j) < r_{m2} \\ [W_b^{(t)}(e_{v_i,v_1}), W_b^{(t)}(e_{v_i,v_2}), \ldots, W_b^{(t)}(e_{v_i,v_{n_3}})] & \text{if} \quad r_{m2} \leq d(v_i, v_j) < r_{m3} \\ 0 & \text{otherwise.} \end{cases} \tag{3.4}$$



(b) $r_{max} = 1$, $t = 15$ (c) $r_{max} = 2$, $t = 15$ (d) $r_{max} = 3$, $t = 15$

(e) $r_{max} = 1$, $t = 30$ (f) $r_{max} = 2$, $t = 30$ (g) $r_{max} = 3$, $t = 30$

(h) $r_{max} = 1$, $t = 45$ (i) $r_{max} = 2$, $t = 45$ (j) $r_{max} = 3$, $t = 45$

Figure 3.4: An example of appearance on images when applying the dynamic transformation by a set of thresholding, radius $r_{max} = 3$.

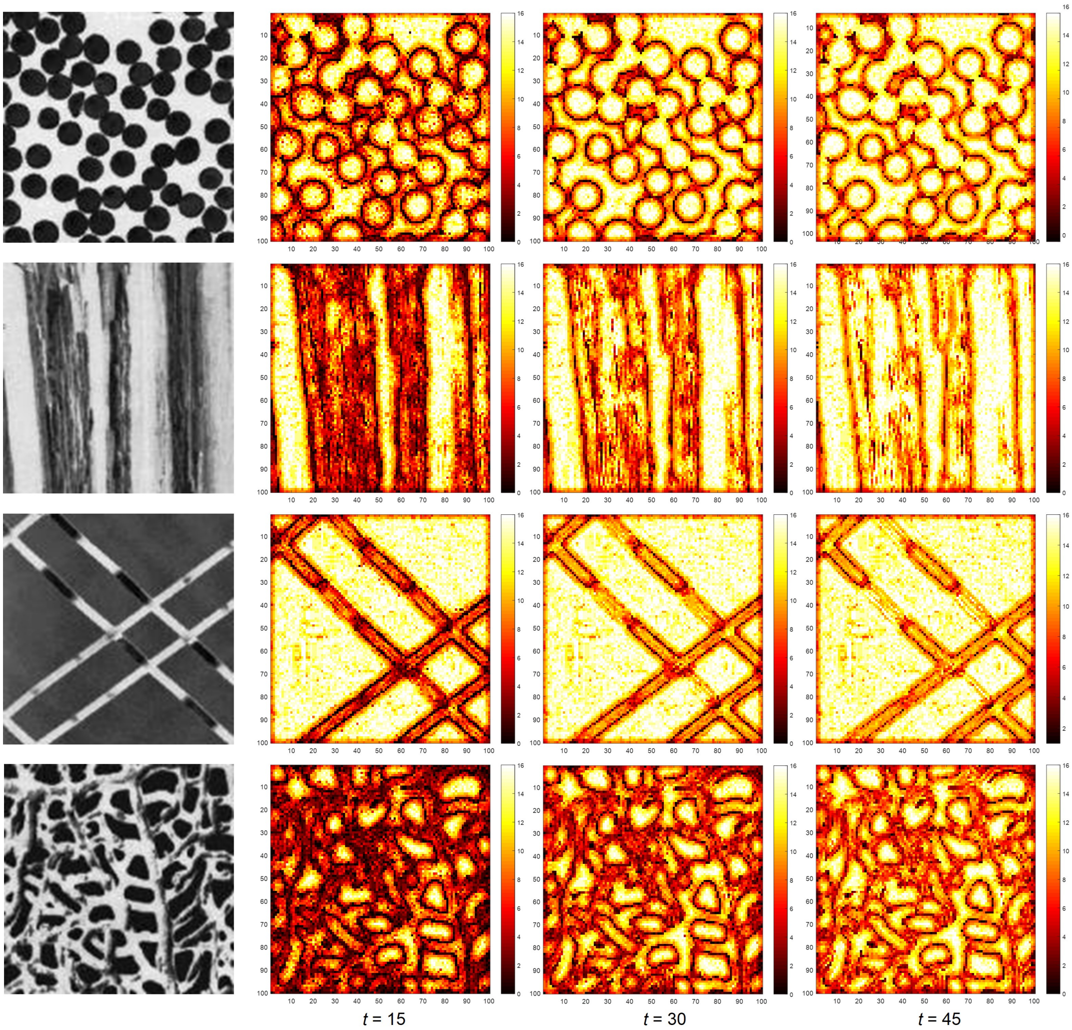


Figure 3.5: Another feature appearance on images when applying the dynamic transformation by a set of thresholding, radius $r_{max} = 3$.

where $v_{n_1}, v_{n_2}$and v_{n_3} are denoted as vertices neighborhood of a vertex v_i in the Euclidean radial distance r_1, r_2 and r_3. In this work, number of the vertices neighborhood, n_1, n_2, and n_3 are equal to 4, 8, and 16, whereas the radial distance r_{m1}, r_{m2} and r_{m3} equal to 1 ,2 and 3, respectively.

The Local spatial pattern mapping or LSPM performs a spatial arrangement analysis. The uniformity of LBP mapping [4,83] is adapted for spatial mapping at different radial distances. The LSPM method is used to describe the uniformity of texture primitives when the binary pattern of a binary row record contains at most two bit-wise transitions between 0 and 1 in the same way as uniformity in LBP theory [83]. We define the LSPM method as follows:

$$lspm(e_{v_i,v_j}) = \sum_{j=1}^{p_n} k^{(t)}(e_{v_i,v_j})2^{(j-1)}, \tag{3.5}$$

where n is 4, 8, and 16, respectively. For considering the uniformity of $lspm$, the following equation is used:

$$\text{LSPM}(n_{r_{max}}, r_n) = \begin{cases} lspm(e_{v_i,v_j}) & \text{if } U(lspm(e_{v_i,v_j})) \leq 2 \\ p+1 & \text{otherwise,} \end{cases} \tag{3.6}$$

where U is the uniform pattern of $k^{(t)}(e_{v_i,v_j})$ in equation 3.4, which is determined when the binary pattern of a binary row record contains at most two bit-wise transitions between 0 and 1. For example, the pattern of 00000000 shows the U value of 0, whereas the binary pattern of 11000001 shows U of 2 as justified by [83]. This equation means that if the $lspm(e_{v_i,v_j})$ have $U > 2$, it defines for non-uniform pattern. This step enables us to analyze the uniform pattern of pixel surroundings, which can refer to local texture analysis. In practice, LSPM is implemented by using a look-up table of 2^{p_n} elements. In this case, there are p_n+2 output bits for each final histogram. The feature properties as histogram for the radial analyses LSPM(p_n, r_n) are defined as follows:

$$F^{(t)}(v_i) = \begin{bmatrix} \text{LSPM}(4,1) \\ \text{LSPM}(8,2) \\ \text{LSPM}(16,3) \end{bmatrix}^{\top}. \tag{3.7}$$

In order to evaluate our proposed method, a discrimination function for texture classification was generated by a nearest neighborhood. In the implementation of this

Databases	Resolution	Classes	#images in Total	Description
Brodatz	128x128	100 classes, 12 images per class	1200	Lack of intra-class variations
UIUC	128x128	25 classes, 40 images per class	1000	Strong scale, rotation and viewpoint changes, non-rigid deformation, material contents
KTH-TIPS	128x128	10 classes, 81 images per class	810	Illumination changes, mall rotation changes, large scale changes
UMD	128x128	25 classes, 40 images per class	1000	Strong scale, rotation and viewpoint changes, object contents

Figure 3.6: Summary of various properties of important texture databases

work, the *Classification Learner* app of MATLAB 2016a version with default parameter values was used for classification following 10-fold cross-validation.

3.4 Experiments

In the present study, three experiments were conducted to compare the results between the original complex network texture descriptor (CNTD) by [16] [1] and our proposed method. The first experiment was a comparison of threshold sets as represented in Table 3.1. The objective of this experiment was to select the best threshold sets by using Brodatz as the validation database. The second experiment examined combinations of feature descriptors by using the threshold set selected from the first experiment. Along with Brodatz, this experiment used the additional three texture databases, UIUC, KTH-TIPS, and UMD, in the evaluation. The summarized features of databases are listed in Fig. 3.6. In this thesis, we built the new Brodatz dataset by cropping 12 subsections with non-overlapping of a larger Brodatz image. Thus it is difficult for us to distinguish some images between each class. The last experiment was a comparison between other conventional methods including LBP, $\mathrm{LBP}^{\mathrm{riu2}}$, and CNTD [16], with the proposed method.

[1] In the experiments, the texture features obtained by using only the degree of node (Deg) approach instead of using statistical descriptors i.e., mean, contrast, energy, and entropy as applied in [16]

3.5 Results and Discussions

3.5.1 Parameter analysis

Table 3.1: Result for the proposed method for different thresholds set. Using r = 1,2,3 for Brodatz database.

Set	Thresholds			No. of descriptors	Success rate [%]	
	t_0	t_{step}	t_{final}		LSPM (proposed)	CNTD
T1	5	5	85	578	88.13 ± 12.02	80.72 ± 15.80
T2	90	5	170	578	68.86 ± 21.82	70.38 ± 20.65
T3	175	5	255	578	19.39 ± 35.72	26.11 ± 35.88
T4	5	10	85	306	87.78 ± 12.49	80.98 ± 16.68
T5	90	10	170	306	69.23 ± 21.40	70.37 ± 20.79
T6	175	10	255	306	20.26 ± 35.95	27.16 ± 35.81
T7	5	15	80	204	87.62 ± 12.28	81.10 ± 16.39
T8	85	15	160	204	72.62 ± 20.06	71.80 ± 19.73
T9	165	15	240	204	24.50 ± 33.98	32.25 ± 33.71
T10	5	15	95	238	87.50 ± 12.41	80.98 ± 16.39

Regarding [16], the proposed approach suggests that the features determined by degree histograms might be able to perform texture discrimination. There is radius r and a set of threshold T are defined as parameters, which must be applied to the networks. Based on the description of the method, both radius r and the set of threshold t are crucial parameters to be configured. First, we start by analyzing the behavior of the method for different threshold sets using a constant radius $r_{max} = 3$ in the Brodatz dataset. Table 3.1 summarizes the results for 10 different configurations of thresholds $(T1, T2, \ldots, T10)$. To compose each set of thresholds, the process was determined by the original model of [16]. The set of threshold considered an initial threshold (t_0), which is constantly increased by a value (T_{step}) until to a final threshold (t_{final}). In the Table 3.1, we split the range of thresholds into three divers intervals ($T1, T2$ and $T3$) with using the same t_{step} value in each interval. This test is performed in order to verify each interval of thresholds which concentrate with the most meaningful information based on the topological structure of the network. The comparison results among threshold intervals show that the most meaningful information could be extracted when

$t < 170$. The initial interval of threshold $T1$ holds the main information about the texture pattern from both methods, LSPM and CNTD, compared with $T2$. Increments $t_{step} = 10$ and $t_{step} = 15$ were evaluated. While configurations from $T4$ to $T9$ present the results of this test. This increased value was followed by a decrease in the number of descriptors which can be indicated by the presence of redundant features in the descriptors computed for $t_{step} = 5$.

3.5.2 Comparison of results from different threshold sets

The best threshold sets were selected to evaluate the methods in different databases including Brodatz, UIUC, KTH-TIPS, and UMD. The configurations $T1, T4, T7$ and $T10$ were chosen for evaluating in this experiment. The success rates of LSPM method and CNTD were listed in Table 3.2 and 3.3, respectively.

Table 3.2: Experimental results of LSPM feature descriptor in different set of thresholds from the texture databases

Databases	T1	T4	T7	T10	Averages
Brodatz	88.13 ± 12.02	87.78 ± 12.49	87.62 ± 12.34	87.50 ± 12.41	87.76 ± 12.32
UIUC	76.91 ± 4.78	76.50 ± 4.69	76.65 ± 4.75	75.43 ± 4.67	76.37 ± 4.72
KTH-TIPS	89.27 ± 1.14	89.14 ± 1.18	88.22 ± 1.21	87.88 ± 1.22	88.63 ± 1.19
UMD	91.78 ± 2.87	91.60 ± 2.86	91.98 ± 2.92	91.45 ± 3.02	91.70 ± 2.92

Table 3.3: Experimental results of CNTD feature descriptor in different set of thresholds from the texture databases

Databases	T1	T4	T7	T10	Average
Brodatz	80.72 ± 15.80	80.98 ± 16.68	81.10 ± 16.39	80.98 ± 16.39	80.94 ± 16.31
UIUC	70.44 ± 5.49	70.70 ± 5.41	68.89 ± 5.61	69.52 ± 5.48	69.89 ± 5.49
KTH-TIPS	84.80 ± 1.29	84.50 ± 1.32	84.90 ± 1.29	84.73 ± 1.31	84.73 ± 1.30
UMD	90.01 ± 2.98	89.90 ± 3.02	89.03 ± 3.11	89.48 ± 3.10	89.60 ± 3.05

The accurate classification result for different set of thresholds from four databases, Brodatz, UIUC, KTH-TIPS, and UMD, achieved similar accurate classification rates of LSPM and CNTD approaches, as listed in Table 3.2 and 3.3, respectively.

In the results from each configuration, different threshold sets will be described in following each dataset. Firstly, Brodatz texture database, the best accuracy result from

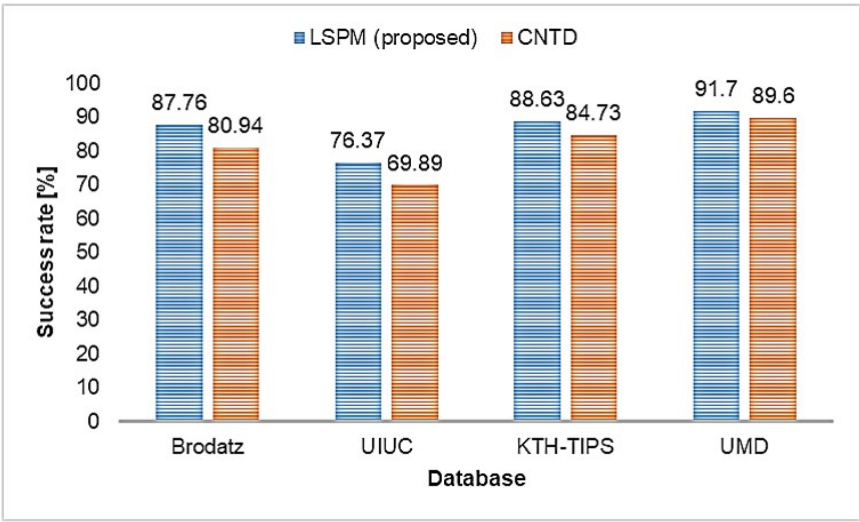


Figure 3.7: Summarize column chart results from LSPM and CNTD methods from Table 3.2 and 3.3

the LSPM approach achieved a success rate of 88.13% for the configurations $T1$, whereas the result of the comparison CNTD approach achieved classification rate of 81.10% for $T7$. As the results have listed in Table 3.2 and 3.3, we can see all configurations $T1, T4, T7, T10$ have similarity achieved the success rates. The average success rate results achieved the rates of 87.76% for LSPM and 80.94% for CNTD approaches. Secondly, UIUC database, the best accuracy results were 76.91% by $T1$, and 70.44% by $T4$ from LSPM and CNTD approaches, respectively. The average success rate results achieved rates of 76.37%, and 69.89% for LSPM and CNTD approaches. The next one is KTH-TIPS database. The accurate classification result for the best set of a threshold by using LSPM approach achieved rate of accuracy 89.27% for the configurations $T1$. The accurate results from the CNTD approach also achieved the highest classification rates of 84.90% for the configurations $T7$. The average success rates results were 88.63% for LSPM and 84.73% for CNTD approach. Finally, UMD database, all the accurate classification results from all configurations $T1, T4, T7, T10$ have similarity achieved the success rates in the LSPM approach, the best results was 91.98% from $T7$. While the CNTD approach achieved the best classification rate of 90.01% from $T1$.

The average success rate results are summarized as column chart in Fig 3.7. The result showed that the LSPM approach could improve classification rates significantly

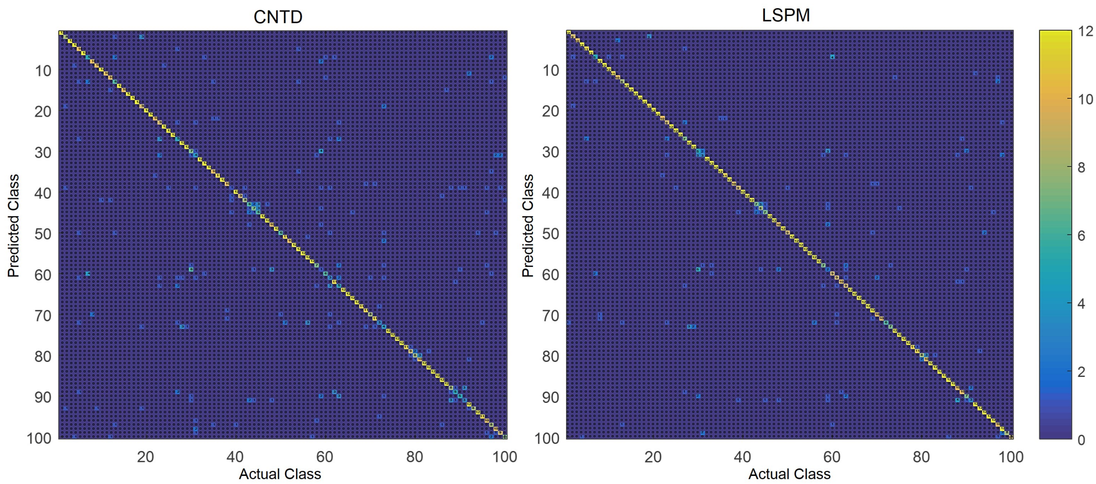


Figure 3.8: Confusion matrix results from Brodatz database

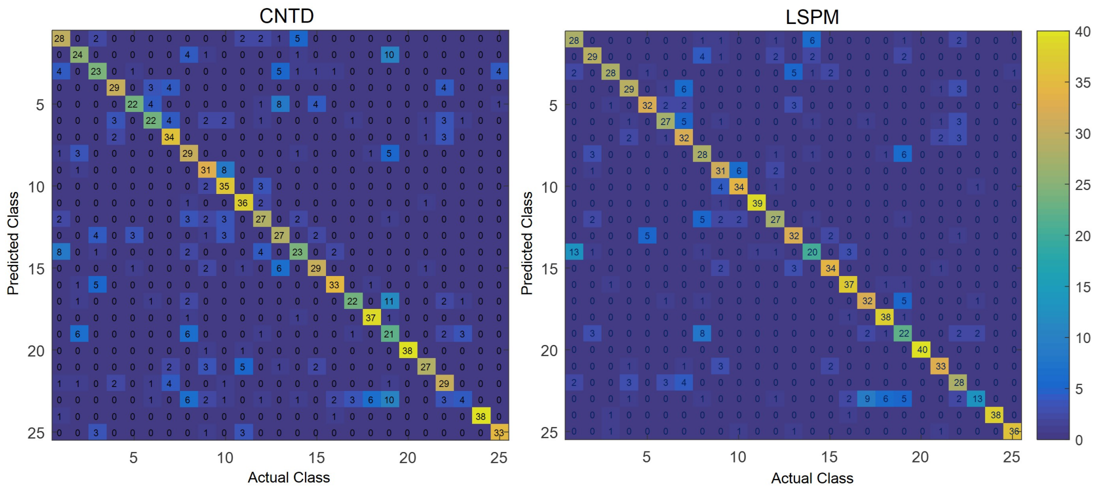


Figure 3.9: Confusion matrix results from UIUC database

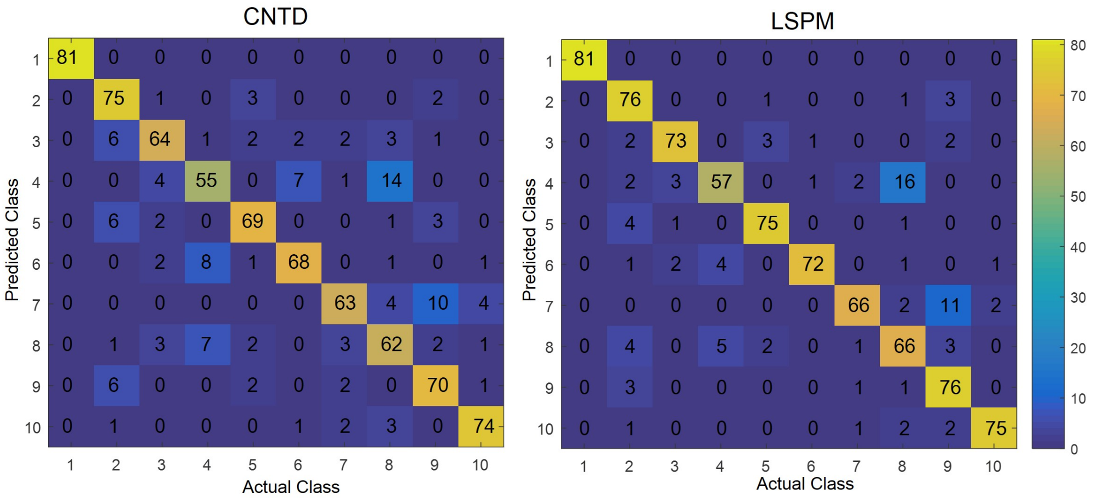


Figure 3.10: Confusion matrix results from KTH-TIPS database

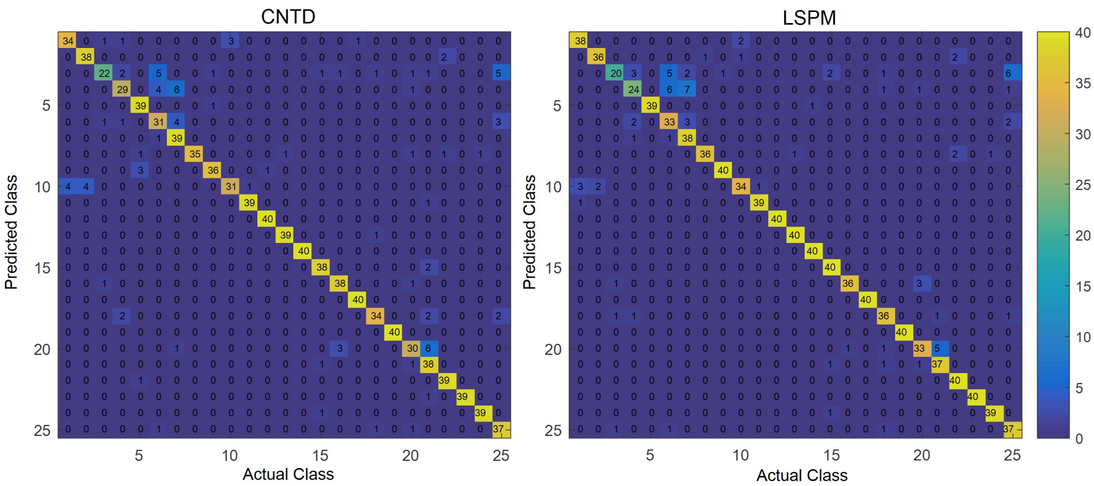


Figure 3.11: Confusion matrix results from UMD database

Table 3.4: Result for the proposed method for different radius values for the Brodatz database.

Radius	Thresholds			No. of descriptors	Success rate [%]	
	t_0	t_{step}	t_{end}		LSPM (proposed)	CNTD
{1}	5	5	85	102	72.51 ± 21.18	69.83 ± 22.09
{1,2}	5	5	85	272	82.61 ± 14.56	78.28 ± 16.61
{1,2,3}	5	5	85	578	88.13 ± 12.02	80.72 ± 15.80

when comparing with the CNTD approach for all evaluated databases. These results can be used to confirm us about how important is the encoding spatial arrangement by LSPM approach. Accordingly, to the LBP^{riu2} mapping, we can see that the local structure pattern information such as microstructure, can be described by this method. Thus, the LSPM approach can be employed for encoding the local structure information. On the other hand, the CNTD method that used a degree of node (Deg) as a feature descriptor in network measurement which this Deg only count the number of value 1s in the binary neighbors' sets instead of encoded them. Moreover, we have shown the confusion matrices results which are demonstrated in Fig. 3.8–3.11, respectively. Regards to these results, the proposed method is shown to be the most effective one for texture characterization, providing an improved classification rate as compared to the original complex network model or CNTD.

3.5.3 Comparison of results from multiple scale analysis

By applying the multiple scale scheme analysis, the better results are shown to be obtained. In this section, we have experimented with comparing classification rates using different radius. As shown in Table 3.4–3.7, the multi-scale of complex network on $r_{max} = 3$ outperformed the classification rates when comparing with other scales. It should be noted that although the r_{max} is strictly equal to 3 in this thesis, achieves much higher classification rates than the original complex network model [16].

3.5.4 Comparison with other texture analysis methods

To further evaluate our proposed method, additional conventional texture analysis methods are chosen for comparison which including LBP and LBP^{riu2} operators [83,87].

Table 3.5: Result for the proposed method for different radius values for the UIUC database.

Radius	Thresholds			No. of descriptors	Success rate [%]	
	t_0	t_{step}	t_{end}		LSPM (proposed)	CNTD
{1}	5	10	85	102	58.80 ± 6.52	57.25 ± 6.53
{1,2}	5	10	85	272	70.40 ± 5.68	66.70 ± 5.60
{1,2,3}	5	10	85	578	76.49 ± 4.69	70.71 ± 5.41

Table 3.6: Result for the proposed method for different radius values for the KTH-TIPS database.

Radius	Thresholds			No. of descriptors	Success rate [%]	
	t_0	t_{step}	t_{end}		LSPM (proposed)	CNTD
{1}	5	5	85	102	76.90 ± 1.81	74.27 ± 1.97
{1,2}	5	5	85	272	87.20 ± 1.23	83.00 ± 1.45
{1,2,3}	5	5	85	578	89.27 ± 1.14	84.80 ± 1.29

Table 3.7: Result for the proposed method for different radius values for the UMD database.

Radius	Thresholds			No. of descriptors	Success rate [%]	
	t_0	t_{step}	t_{end}		LSPM (proposed)	CNTD
{1}	5	5	85	102	83.25 ± 4.16	78.60 ± 4.63
{1,2}	5	5	85	272	90.42 ± 2.99	87.24 ± 3.16
{1,2,3}	5	5	85	578	91.78 ± 2.87	90.10 ± 2.98

In the experiment, the LBP descriptor was computed by the concatenation of the histograms when (P, R) = (8,2) to characterize a texture pattern, and results in a total of 256 descriptors. The LBP^{riu2} descriptor was computed by the concatenation of the histograms when (P, R) = (8,1), (16,2), (24,3) to characterize a texture pattern, and results in a total of 54 descriptors.

For comparing with other methods, Principal Component Analysis (PCA) is applied to downsize the feature space purpose [54] on the proposed methods. We denoted CNTD, and LSPM approaches with PCA as CNTD–PCA and LSPM–PCA as listed in Table 3.8. In order to determine optimal range number of principal components in CNTD–PCA and LSPM–PCA, we have set the percentage of the total variance explained by each principal component no more than 99.60%–99.70%, to obtain the optimal number of PCs. Therefore, the optimal number of feature descriptor of CNTD–PCA, and LSPM–PCA were selected as 21 number of features in this experiment.

Table 3.8: Comparison of success rate [%] between other texture analysis methods

Methods	Number of features	Success rate [%]			
		Brodatz	UIUC	KTH-TIPS	UMD
LBP	256	85.16 ± 15.70	66.53 ± 4.47	96.68 ± 0.59	92.96 ± 2.58
LBP^{riu2}	54	88.28 ± 13.34	82.21 ± 4.22	95.63 ± 0.56	94.52 ± 1.70
CNTD	578	80.72 ± 15.80	70.44 ± 5.49	84.80 ± 1.29	90.10 ± 2.98
LSPM	578	88.13 ± 12.02	76.91 ± 4.78	89.27 ± 1.14	91.78 ± 2.87
CNTD—PCA	21	84.12 ± 13.38	75.42 ± 4.44	86.79 ± 1.08	92.72 ± 2.07
LSPM—PCA	21	86.28 ± 11.87	77.25 ± 4.35	89.38 ± 0.99	94.06 ± 2.13

Based on Table 3.8, we will discuss the results one by one for each database. By applying the PCA for reducing dimensional feature space, CNTD–PCA obtained better results than CNTD in all databases. For Brodatz database, LBP^{riu2} and LSPM achieved the best success rate of 88.28% and 88.13% respectively. By comparing with CNTD and LSPM, we can see that the proposed LSPM method could be used for enhancing the original complex network model for texture classification. For the UMD database, the proposed method achieved similar classification rate with other methods. On the other hand, the UIUC database which included different viewpoints with perspective distortion and non-rigid transformation, LBP^{riu2} methods outperformed the other methods by 82.21%. These points can indicate the local features using the LBP can be promising for improving our approach. For KTH-TIPS, the LBP and LBP^{riu2} is shown to be the best results than others.

Accordingly, it can be concluded from experiment results that, for CNTD and LSPM features, classification accuracy on LSPM from all databases are significantly improved by the CNTD method. The encoding spatial arrangement of distribution of local pixels, then the spatial structure information which is visual micro-structure (e.g., edge, line, spots) can be more detectable on local image texture. The encoding spatial arrangement is more robust than the degree of node connectivity for uncontrolled environment database.

3.5.5 Robustness in uncontrolled environments

In the last subsection, the characteristics of complex-based network have been discussed in terms of different configuration-wise aspects and also the benchmarking of the proposed method with other texture analysis approaches. This section also introduces the results concerning the robustness in uncontrolled environments of the method such as rotation, scale changed, and viewpoint distortion. These issues are the essential and desirable characteristics in texture recognition applications.

Fig. 3.12 – Fig. 3.15 show the results achieved for CNTD and proposed method when it was applied to the rotation, scale changed and viewpoint variation texture databases. The multiple scale analysis is applied for capturing local textural information. The histogram at bins 1–6 is corresponding results when radius r equal to 1, at bins 7–16 is corresponding results when radius r equal to 1, and at bins 17–34 is corresponding results when radius r equal to 3. The proposed feature LSPM performs encoding spatial arrangement of the binary neighbor sets in order to remove the effect of rotation as explained in Section 3.3.1. Based on the features in Fig. 3.12, the proposed features in rotated texture images are nearly the same. To be more understandable, we have shown the Chi-square value (χ^2) for calculating the distance between two histograms of intra-class from databases. The proposed features can show the minimum values rather than the CNTD features.

Fig. 3.13 illustrated the features as textures acquired from different viewpoints. The results showed that the two features are nearly the same. As the Fig. 3.9, the LSPM method showed a higher rate of predictable class than the CNTD, which may

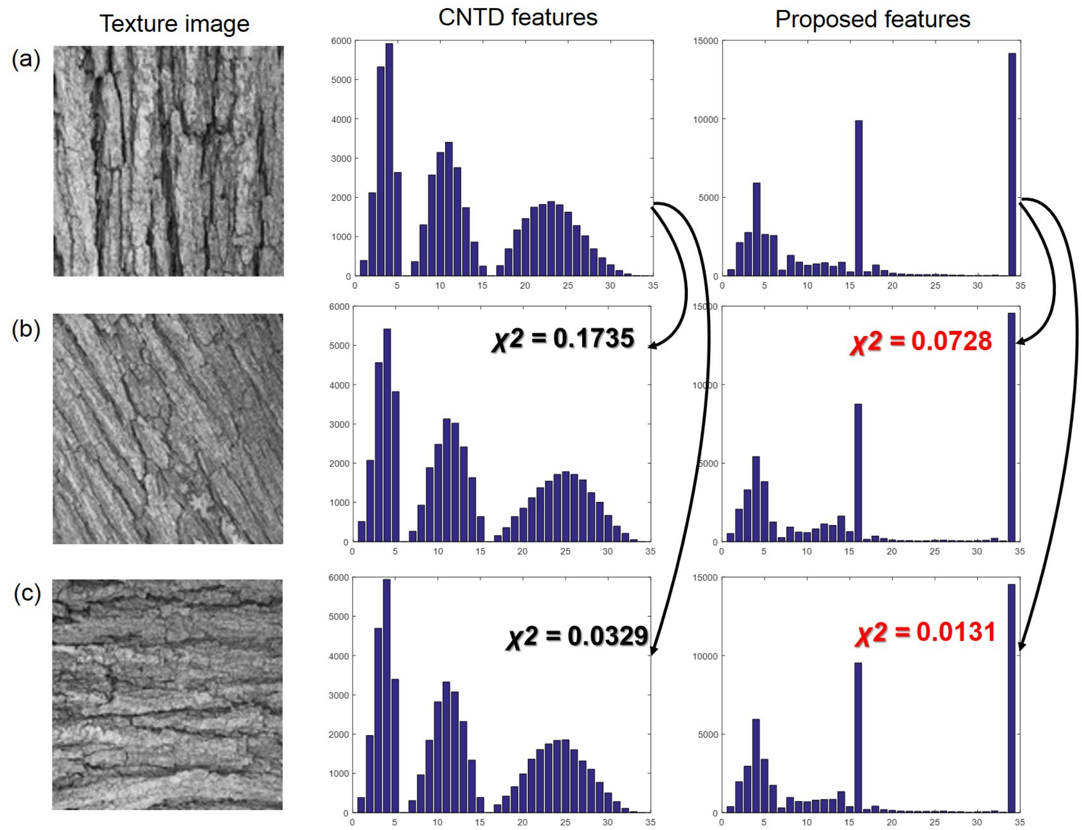


Figure 3.12: 1st column: Texture image at orientations 0°, 30° and 90°. 2nd column: bins 1 - 34 of the corresponding concatenate histograms from r_1, r_2, r_3 by the CNTD features. 3rd column: bins 1 - 34 of the corresponding concatenate histograms from r_1, r_2, r_3 with $t = 20$ by the proposed features

result from the effect of rotation removal. However, the local discriminative information is required for improving the classification performance.

For scale invariance, the feature results in Fig. 3.14 and Fig. 3.15 can prove the superiority of our proposed method. Although the proposed method was not better than the LBP based methods in UIUC, KTH-TIPS and UMD databases, we obtained better results than the CNTD. The network model is derived from the Euclidean distance between pixels and, in discrete space a small error is added because the Euclidean distance is not a constant at all rotation angles. The proposed approach also considered the intensity of the pixel as information to compose the edge weight in Eq. (2.1). Its value does not change during image rotation and, in association with the normalization step, therefore, it diminishes the rotation error created by the Euclidean distance, and making the proposed method relatively more robustness and tolerance to noise.

3.6 Summary

In Chapter 3, we proposed a new method in image texture characterization based on a complex network model for texture classification. Local spatial pattern mapping (LSPM) approach proposed for encoding spatial distribution of local pixels in the complex network-based model. The multi-scale analysis in the complex network-based model can improve classification performance. The deterministic graph in texture representation should be investigated to be more discriminative information for increasing performance of classification. (discussed in Chapter 4). The experimental results show that the performance of LSPM in analyzing spatial information based on a complex network model improves the accuracy of texture classification as compared to the original complex network-based model (CNTD).

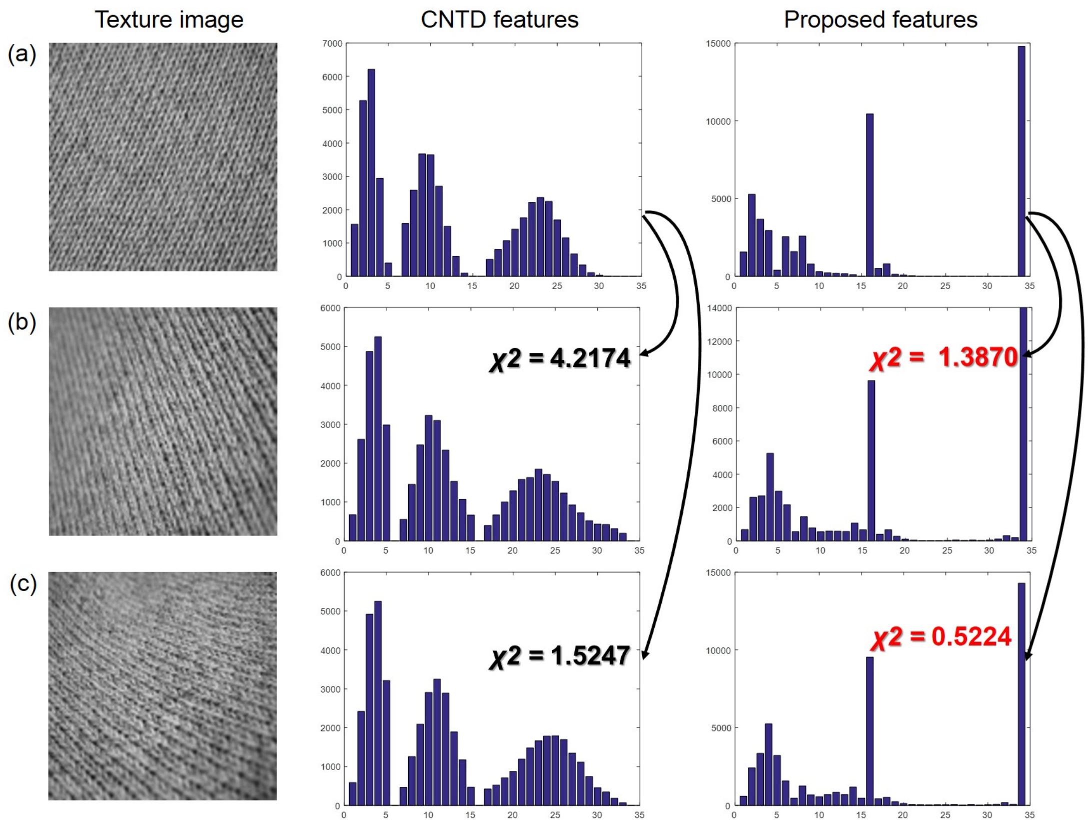


Figure 3.13: 1st column: Texture image at viewpoint variation from UIUC database. 2nd column: bins 1 - 34 of the corresponding concatenate histograms from r_1, r_2, r_3 by the CNTD features. 3rd column: bins 1 - 34 of the corresponding concatenate histograms from r_1, r_2, r_3 with $t = 20$ by the proposed features

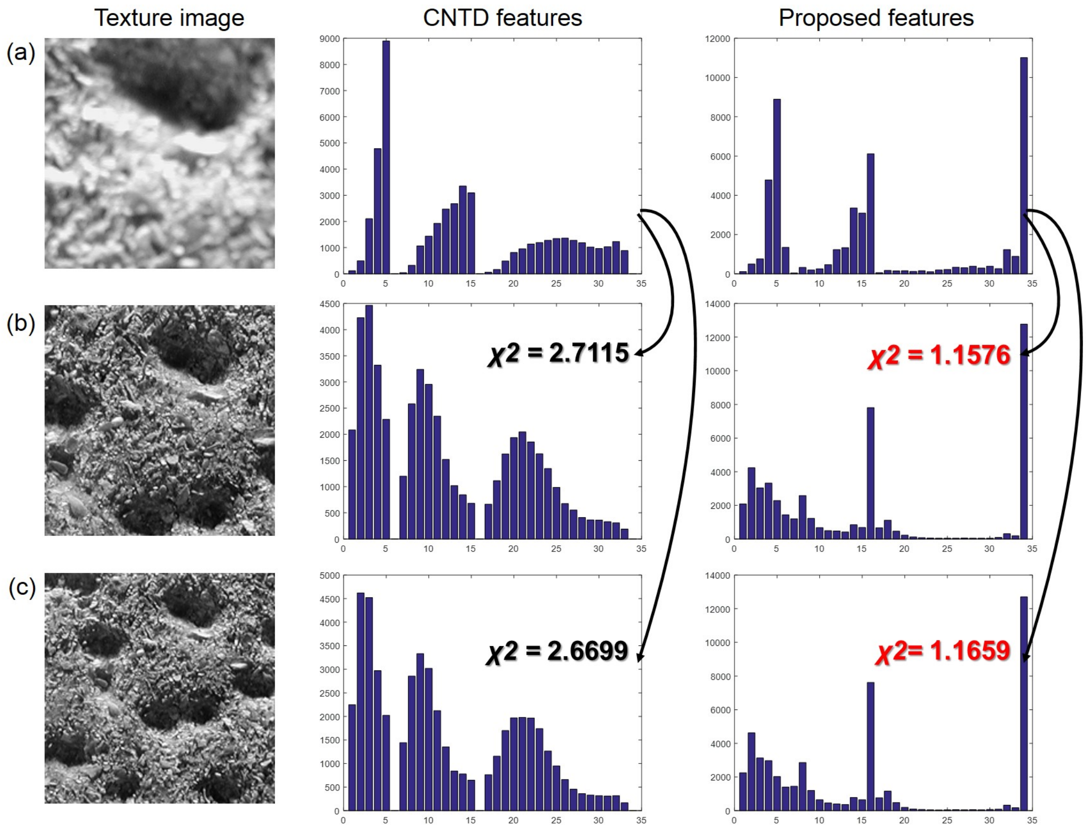


Figure 3.14: 1st column: Texture image at scale changed from KTH-TIPS database. 2nd column: bins 1 - 34 of the corresponding concatenate histograms from r_1, r_2, r_3 by the CNTD features. 3rd column: bins 1 - 34 of the corresponding concatenate histograms from r_1, r_2, r_3 with $t = 20$ by the proposed features

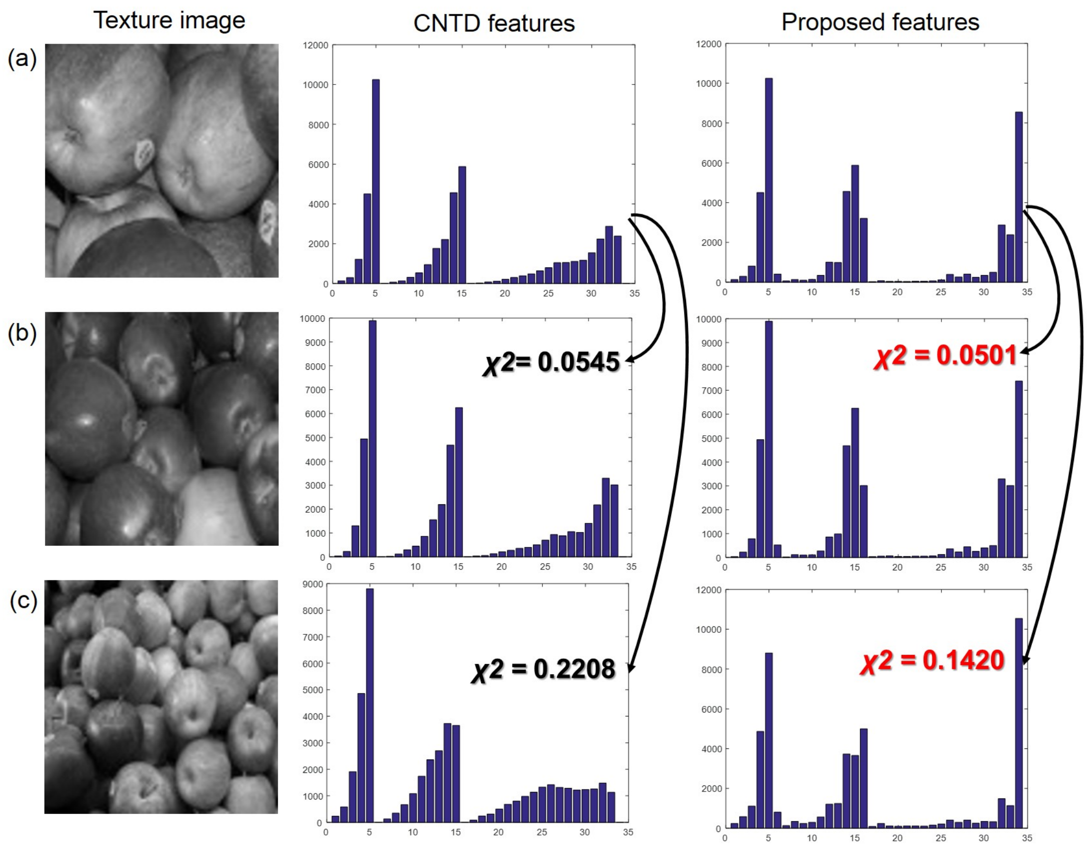


Figure 3.15: 1st column: Texture image as an object has viewpoint and scale variation from UMD database. 2nd column: bins 1 - 34 of the corresponding concatenate histograms from r_1, r_2, r_3 by the CNTD features. 3rd column: bins 1 - 34 of the corresponding concatenate histograms from r_1, r_2, r_3 with $t = 20$ by the proposed features

Chapter 4

Graph-based Representation in Texture Analysis

4.1 Introduction

Graph-based representation has been approached for texture characterization based on complex network model [42] which can be used to describe image structures. According to Chapter 3, we proposed the local spatial pattern mapping (LSPM) approach as a new graph connectivity measurement by encoding the spatial information in the complex network model. The approach adopted a scheme idea of the local binary pattern [83] to investigate the spatial arrangement of vertices for enhancing the original complex network model [16]. The results are shown to be an effective method by using the interaction between the spatial arrangement in which was inspired by the LBP and the complex network model for texture classification. However, the local discriminative information is required for improving classification performance.

Based on the graph theory, the image pixels can be represented by the set of vertices and the set of edges. The weight of edge where generated for describing the topology of a graph can be used to describe the image structure by a pairwise connection. This value importantly employs for representing the information on the image texture, and hence the deterministic the weighted graph is focused on this chapter. The difference of local pixels is used to obtain the weight of edges. However, the necessary edge of weight property such as the direction is discarded from the numerical value of the weighted edges. Regarding the standard pattern recognition techniques such as LBP operator,

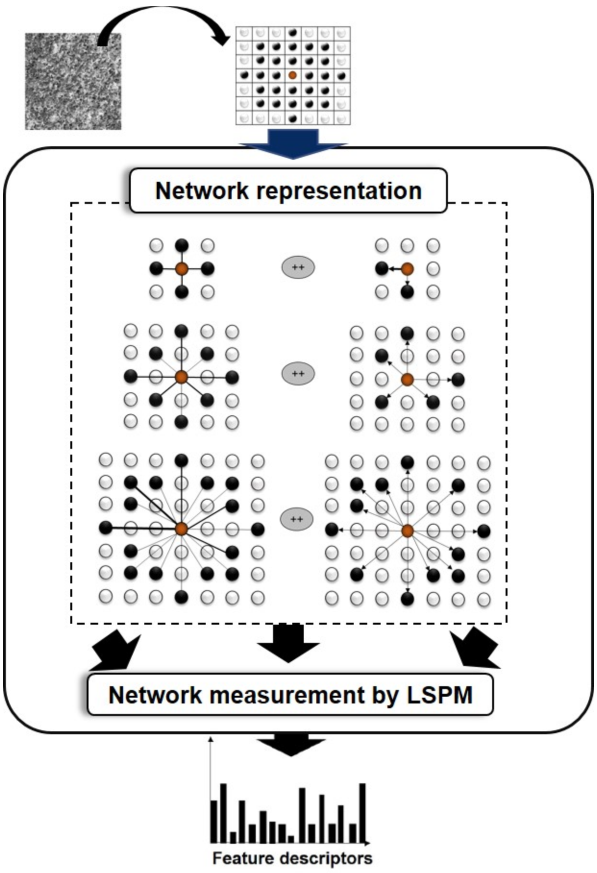


Figure 4.1: The general framework of graph-based spatial vector for texture analysis and classification.

many methods have proposed for extending the basic LBP operator. A scheme idea method that inspiring us for developing this work is CLBP method. Zhenhua et al. [49] proposed completed modeling of LBP (CLBP) operator for texture classification. The fundamental idea of this technique is a decomposition of two complementary component which including the sign and the magnitude features for extracting the texture information

Fig. 4.1 represents an overview of the general framework of a graph-based representation for texture characterization. The deterministic graph modeling is focused in this chapter for analyzing and extracting meaningful information in local texture images. The spatial arrangement of graph connectivity has approached for vertex measurement. To summarize, the main contributions of this chapter can be described as follows:

1. Deterministic graph modeling of the complex network is developed with increased performance in order to sufficiently extract discriminative information for texture classification;

2. The extracted local discriminative information outperformed the results in Chapter 3 and also conventional texture analysis;

3. The local grayscale difference and the local structure distributions features are combined within a proposed deterministic graph modeling;

4. The developed deterministic graph modeling can achieve better performance in uncontrolled environments in terms of rotation, scale changed and viewpoint distortion when compared the results in Chapter 3

5. The graph-based representation is employed as a new feature descriptor for clothing category classification [97].

The rest of this chapter is organized as follows: The architecture of the proposed graph-based representation for texture analysis is introduced in Section 4.2 and 4.3. Section 4.4 describes the vertex measurement which is used in the experiments. The experiments and texture databases are presented in Section 4.5. Results and discussion in our proposed model are detailed in Section 4.6. Finally, the application to clothing images is demonstrated in Section 4.7.

4.2 Graph-based image representation

Graph structure is a principle idea for image representation which reflects the structure context of the input image. Fig. 4.2 illustrates designing graph by using distance-based approach. This is the simplest way to represent information about an image on a per-pixel basis. An image I with a resolution of $M \times N$ pixels. Each pixel p_n of a gray image is characterized by an integer value g which have intensity values between $0-255$, $I(p_n) \in [0, 255]$, where n is a finite number of pixels equal to $1, 2, \ldots M \times N$. Suppose $I(i, j) = g$, $i = 1, \ldots, M$ and $j = 1, \ldots, N$ where i and j are the Cartesian coordinate of the pixel $I(p_n)$. Let $G = (V, E)$ is a graph comprising the set of vertices V and the set of edges E which each pixel $I(i, j)$ is considered as a vertex $v_{ij} \in V$. The two vertices

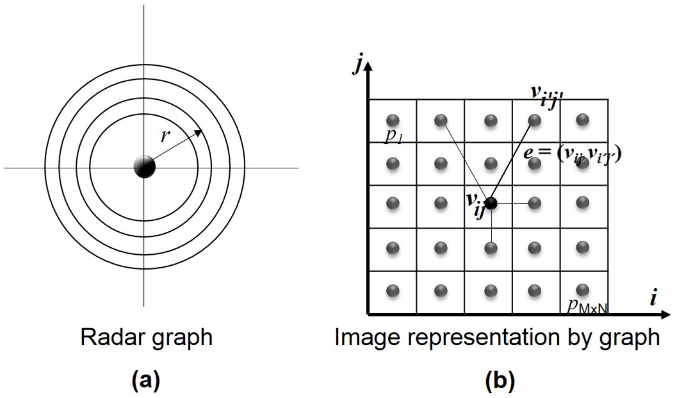


Figure 4.2: Inspiring graph structure for image presentation.

are connected by a non-direct edge $e \in E, e = (v_{ij}, v_{i^{'}j^{'}})$, when the Euclidean distance between two vertices is less than or equal to value r as represented in equation 4.1.

$$E = \{e = (v_{ij}, v_{i'j'}) \in I \times I \| \sqrt{(i - j')^2 + (i - j')^2} \leq r\}. \tag{4.1}$$

4.3 The deterministic graph structure

4.3.1 Weight of edges

The weight of edges is used for representing a structure which pairwise connections have some numerical values. The simple data structure of an image is pixel information which including color value and coordination. A difference of pixel intensities defines the weight of graph, that is, co-occurrence pixels of a difference of intensity can be used for constructing the weight of edges, and consequently this approach can characterize the local image textures. For each non-directed edge $e \in E$, we associate a weight $W(e)$, which is defined by the difference of intensity between a pixel $I(i, j)$ and its neighbors when $d(v_{ij}, v_{i'j'}) \leq r$. The weight of edges is given by:

$$W(e) = \begin{cases} I(i,j) - I(i^{'}, j^{'}) & \text{if } d(v_{ij}, v_{i'j'}) \leq r \\ 0 & \text{otherwise ,} \end{cases} \tag{4.2}$$

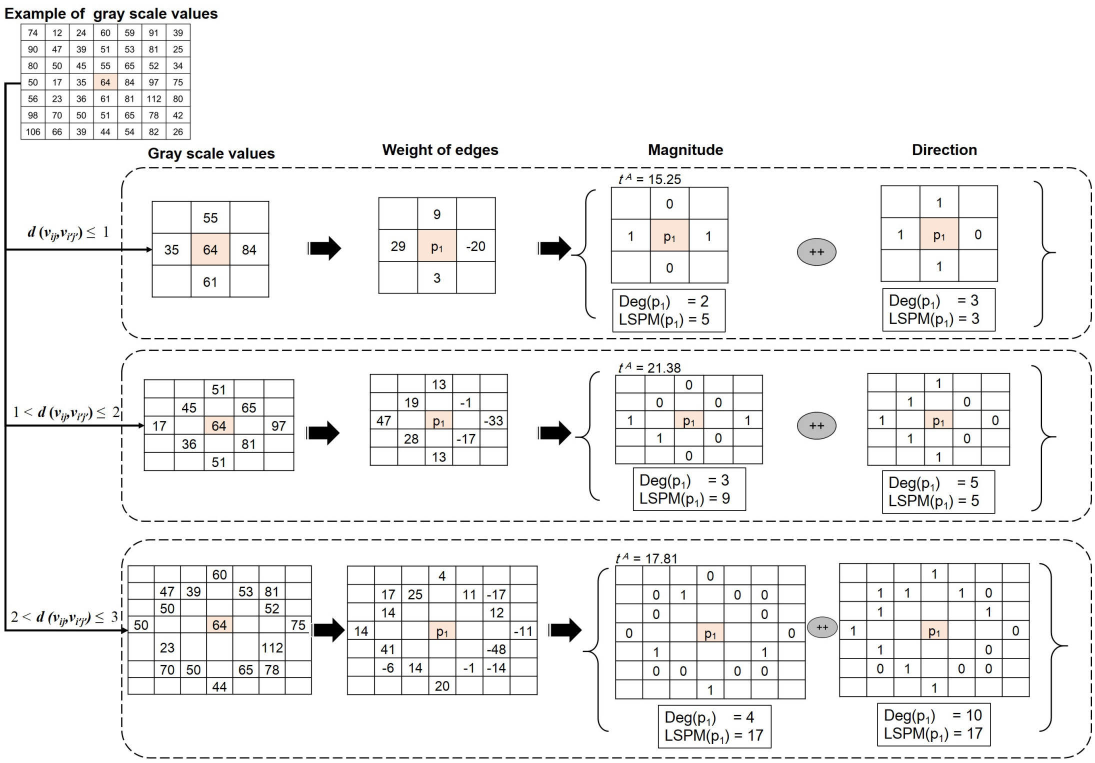


Figure 4.3: An example of the binary transformation by spatial vector. (radius $r_{max} = 3$)

4.3.2 Binary pattern transformation by spatial vector

This chapter considers the edges as a spatial vector that has a magnitude and direction properties as illustrated in Fig.4.4. The magnitude can be referred as non-direct edges for a graph, whereas the direction refers to arrows in the graph. We define the magnitude of the weighted graph by obtaining an absolute of the weighted graph value. The sign of weighted graph value is used for determining the direction of an edge. The binary pattern transformation can generate by thresholding. For the magnitude value, this approach has required a threshold for generating the binary pattern, whereas the sign can present by itself. Accordingly, a connected-graph based on magnitude property and a connected-graph based on direction property are defined as the magnitude and the direction of the edges on this work. These two approaches can extract different information on local pixels which are essential for texture analysis. Fig. **??** are demonstrated the binary pattern transformation based on magnitude and direction

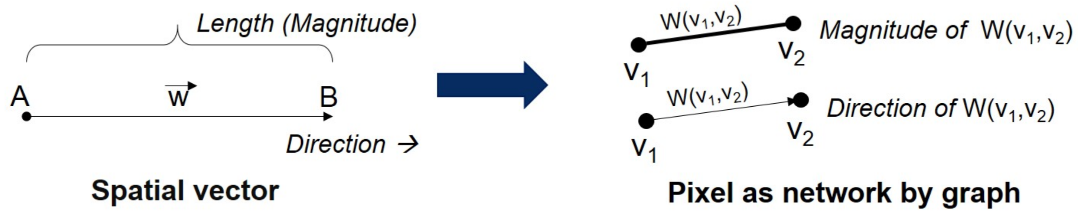


Figure 4.4: A conceptual framework of spatial vector to a pixel as network by graph.

properties.

4.3.2.1 Connected-graph based on magnitude property

To define a threshold value, the auto local thresholding is approached by an average of the absolute weighted graphs values as defined below:

$$t^A(e) = \frac{|(W_1(e) + W_2(e) + \cdots + W_{v'}(e)|}{v'}. \tag{4.3}$$

where v' is number of neighbors of v. The adaptive local thresholding t_{r_n} apply to the original set of edges E for generating a weighted-binary pattern based on magnitude property WB^m, is given by:

$$WB^m(e) = \begin{cases} 1 & \text{if } |W(e)| \leq t^A(e) \\ 0 & \text{otherwise .} \end{cases} \tag{4.4}$$

where t^A is auto local thresholding which is generated by an average of the absolute weighted graphs value in the equation 4.3. This approach is performed by converting the pixels whose weights are less than or equal to threshold t^A to 1, while the remaining pixels are converted to 0.

4.3.2.2 Connected-graph based on direction property

$$WB^d(e) = \begin{cases} 1 & \text{if } sign(W(e)) > 0 \\ 0 & \text{otherwise .} \end{cases} \tag{4.5}$$

4.4 Network measurement

The graph-based image representation described the topology of graphs as we explained above-section. The vertex measurement explains in this section. The degree of node

(Deg) and local spatial pattern mapping (LSPM) are applied for evaluation in this chapter. Based on this two measurement, the final histograms can be obtained to characterize the topology of graphs for texture classification. Fig. 4.5 illustrated an example of image appearances which are constructed by the connected graph based magnitude and direction using Deg method as vertex measurements from Brodatz texture database.

4.4.1 Degree of node (Deg)

The basic topological property of a graph can be obtained regarding the degree (or connectivity) of a vertex in the graph. The degree of a vertex v can be denoted by $deg(v)$ which is the number of graph edges which incident to the vertex. We defined this $deg(v)$ of magnitude and direction properties as follows;

$$deg^m(v) = \sum_{e \in E} WB^m(e), \tag{4.6}$$

$$deg^d(v) = \sum_{e \in E} WB^d(e). \tag{4.7}$$

Based on multiple scale analysis, we have set radial distance $r_{max} = 3$ in the experiment. As an example in Fig. 4.3, The set of graph properties can be given by

$$G_M(v) = [deg^m_{r_1}(v), deg^m_{r_2}(v), deg^m_{r_3}(v)], \tag{4.8}$$

$$G_D(v) = [deg^d_{r_1}(v), deg^d_{r_2}(v), deg^d_{r_3}(v)], \tag{4.9}$$

The final feature vector by using degree of node as a vertex measurement is given by

$$\theta = [H(G_M)H(G_D)]. \tag{4.10}$$

4.4.2 Local Spatial Pattern Mapping (LSPM)

Multi-radial distance analysis is employed for feature representation as we explained in the chapter 3. After the binary pattern transformation, the neighbors of a vertex v_i which have Euclidean radial distance, r_{m1}, r_{m2} and r_{m3} equal to 1, 2, and 3 respectively, are constructed by the radial symmetric neighborhood. This approach enables us to describe local context information about pixel surroundings. Fig. 4.6 illustrated an example of image appearances results of the connected graph based magnitude and direction using LSPM method as vertex measurements from Brodatz texture database.

A spatial texture analysis is performed by local spatial pattern mapping or LSPM. The LSPM method is used to describe the uniformity of texture primitives when the binary pattern of a binary row record contains at most two bit-wise transitions between 0 and 1 in the same way as uniformity in LBP theory [83]. We define the LSPM method as follows:

$$lspm^m(e) = \sum_{n=1}^{v'} WB_n^m(e)2^{(v'-1)}, \tag{4.11}$$

$$lspm^d(e) = \sum_{n=1}^{v'} WB_n^d(e)2^{(v'-1)}, \tag{4.12}$$

where v' is number of neighbors. For considering the uniformity of $lspm$, the following equation is used:

$$\mathrm{LSPM}^m(p_n, r_n) = \begin{cases} lspm^m(e) & \text{if } U(lspm^m(e)) \leq 2 \\ p+1 & \text{otherwise,} \end{cases} \tag{4.13}$$

$$\mathrm{LSPM}^d(p_n, r_n) = \begin{cases} lspm^d(e) & \text{if } U(lspm^d(e)) \leq 2 \\ p+1 & \text{otherwise,} \end{cases} \tag{4.14}$$

where U is the uniform pattern of $WB^m(e)$ and $WB^d(e)$, which is determined when the binary pattern of a binary row record contains at most two bit-wise transitions between 0 and 1. For example, the pattern of 00000000 shows the U value of 0, whereas the binary pattern of 11000001 shows U equal to 2 as justified by [83]. This equation means that if the $lspm(e)$ have $U > 2$, it defines for non-uniform pattern. This step enables us to analyze the uniform pattern of pixel surroundings, which can refer to local texture analysis. In practice, LSPM is implemented by using a look-up table of 2^{p_n} elements. In this case, there are $p_n + 2$ output bits for each final histogram.

$$G'_M(v) = [\mathrm{LSPM}^m(4,1), \mathrm{LSPM}^m(8,2), \mathrm{LSPM}^m(16,3)] \tag{4.15}$$

$$G'_D(v) = [\mathrm{LSPM}^d(4,1), \mathrm{LSPM}^d(8,2), \mathrm{LSPM}^d(16,3)] \tag{4.16}$$

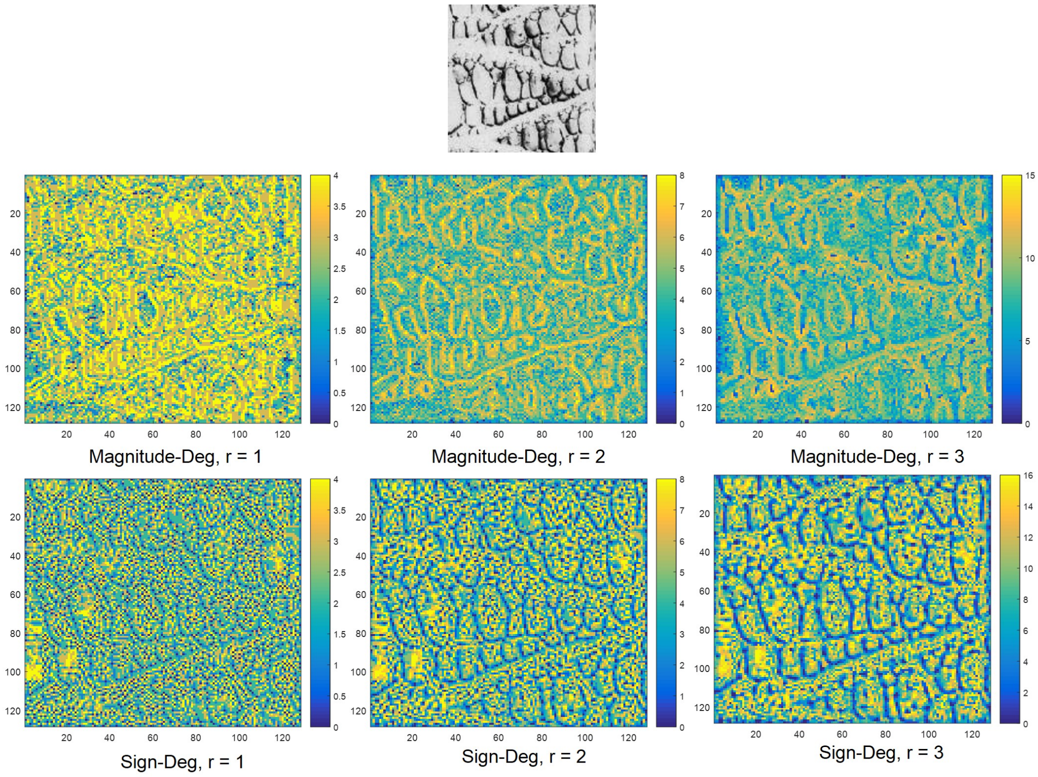


Figure 4.5: An example of image appearances results of the connected graph based magnitude and direction using Deg method as vertex measurements from Brodatz texture database.

In this case, there are p_n+2 output bits for each final histogram. The feature properties as histogram for the radial analyses LSPM(p_n, r_n) are defined as follows:

$$\delta = [H(G'_M)H(G'_D)]. \tag{4.17}$$

4.5 Experiments

In all experiments, the nearest neighborhood with Euclidean distance is used as a discrimination function, following 10-fold cross-validations for texture classification. The simple classifier was chosen rather than a more sophisticated one in order to demonstrate the importance of the features in the classification task.

In this study, three experiments were conducted to compare the results; firstly,

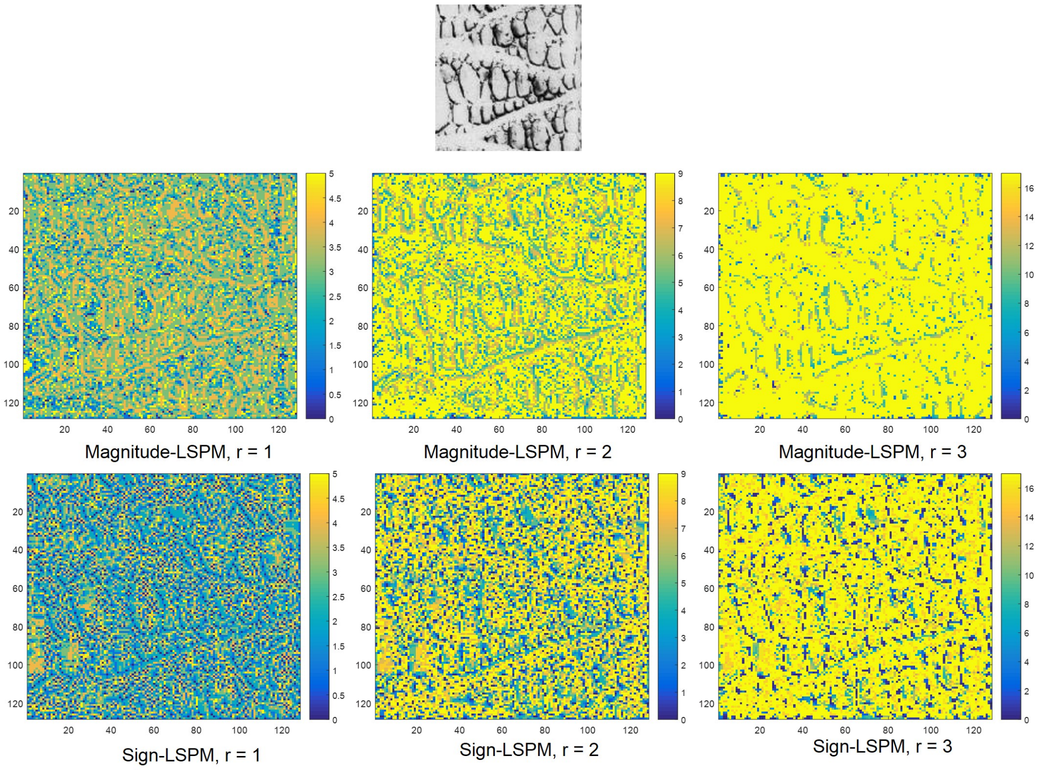


Figure 4.6: An example of image appearances results of the connected graph based magnitude and direction using LSPM method as vertex measurements from Brodatz texture database.

the connected-graph based on magnitude and direction properties; secondly, the combined between magnitude and direction properties; thirdly, the comparison with other methods. Moreover, along with the experiments, we conducted to compare the performance of the system by using the degree of node (deg) and the local spatial pattern mapping (LSPM) as vertex measurement. The results are evaluated by using four texture databases, Brodatz, UIUC, KTH-TIPS, and UMD. The summarized databases are shown in Fig. 4.7.

Databases	Resolution	Classes	#images in Total	Description
Brodatz	128x128	100 classes, 12 images per class	1200	Lack of intra-class variations
UIUC	128x128	25 classes, 40 images per class	1000	Strong scale, rotation and viewpoint changes, non-rigid deformation, material contents
KTH-TIPS	128x128	10 classes, 81 images per class	810	Illumination changes, mall rotation changes, large scale changes
UMD	128x128	25 classes, 40 images per class	1000	Strong scale, rotation and viewpoint changes, object contents

Figure 4.7: Summary of various properties of important texture databases

4.6 Results and discussions

4.6.1 Results of the connected-graph based on magnitude and direction properties

In the experiments, we have set radius $r_{max} = 3$, where $r = \{1, \ldots, r_{max}\}$. It means that radial distance of r_{max} is used to imply the scale of the radial distance pattern mapping as described in equation 4.1. The experimental results are given in Table 4.1 for using the degree of node (Deg) as a vertex measurement and 4.2 for using LSPM approach. For the results of the connected-graph based on magnitude and direction properties that are given in Table 4.1 and 4.2, these approaches showed the connected-graph based on direction properties is more efficient than thresholding in preserving the local difference information. The results performed in the same direction as discussed in [49]. Although the direction property can receive more classification performance, the completely decomposing by magnitude and direction is required to achieve local discriminative information for the classification task. Accordingly, it can assure us that the magnitude and the direction of the spatial vector have influences on texture classification in terms of the graph-based representation.

4.6.2 Comparison results of vertex measurements

The experimental results of each vertex measurement are given in Table 4.1 and 4.2. For the summarize by column chart, Fig. 4.8 illustrate more interesting results. In Chapter

Table 4.1: Success rate [%] results by using Degree of node (Deg).

Descriptors	Deg			
	Brodatz	UIUC	KTH-TIPS	UMD
Magnitude	80.48 ± 17.22	65.47 ± 5.24	89.29 ± 0.96	82.35 ± 4.43
Direction	84.08 ± 16.25	78.15 ± 3.81	89.44 ± 1.04	86.97 ± 3.34
Combined	89.13 ± 11.98	85.11 ± 2.86	95.96 ± 0.66	91.21 ± 2.85

Table 4.2: Success rate [%] results by using Local Spatial Pattern Mapping (LSPM).

Descriptors	LSPM			
	Brodatz	UIUC	KTH-TIPS	UMD
Magnitude	83.79 ± 16.60	70.63 ± 5.11	88.57 ± 1.06	80.27 ± 3.85
Direction	89.68 ± 13.60	84.96 ± 3.40	96.19 ± 0.58	94.68 ± 1.81
Combined	90.92 ± 12.02	87.92 ± 2.67	96.56 ± 0.49	92.65 ± 2.26

3, we have discussed how important of encoding spatial distribution from the resulting of topology graphs which demonstrated the outperformed results the degree of node (Deg) in the original complex network model for texture analysis by [16]. Therefore, the LSPM descriptor is proposed a new graph connectivity measurement, instead of using the degree of node (Deg) [36]. As Fig. 4.8 (a) and (b), the results have shown that the combined properties achieve more classification rate than only magnitude and direction property. For Fig. 4.8 (c) illustrated comparison between a degree of node and a LSPM descriptor results. Based on the results made us realized how the efficiency of the local discriminative information from the connected graphs because the results are shown similarity achieve classification rates. Therefore, we can conclude that for seeking more local discriminative information, the deterministic of a weighted graph is importantly effecting to the model.

4.6.3 Comparison with other methods

For more evaluate our proposed method, the additional conventional texture analysis methods chosen for comparison which including, LBP and LBP^{riu2} operators were chosen in this experiment [83,87], and the completed local binary pattern (CLBP) [49].

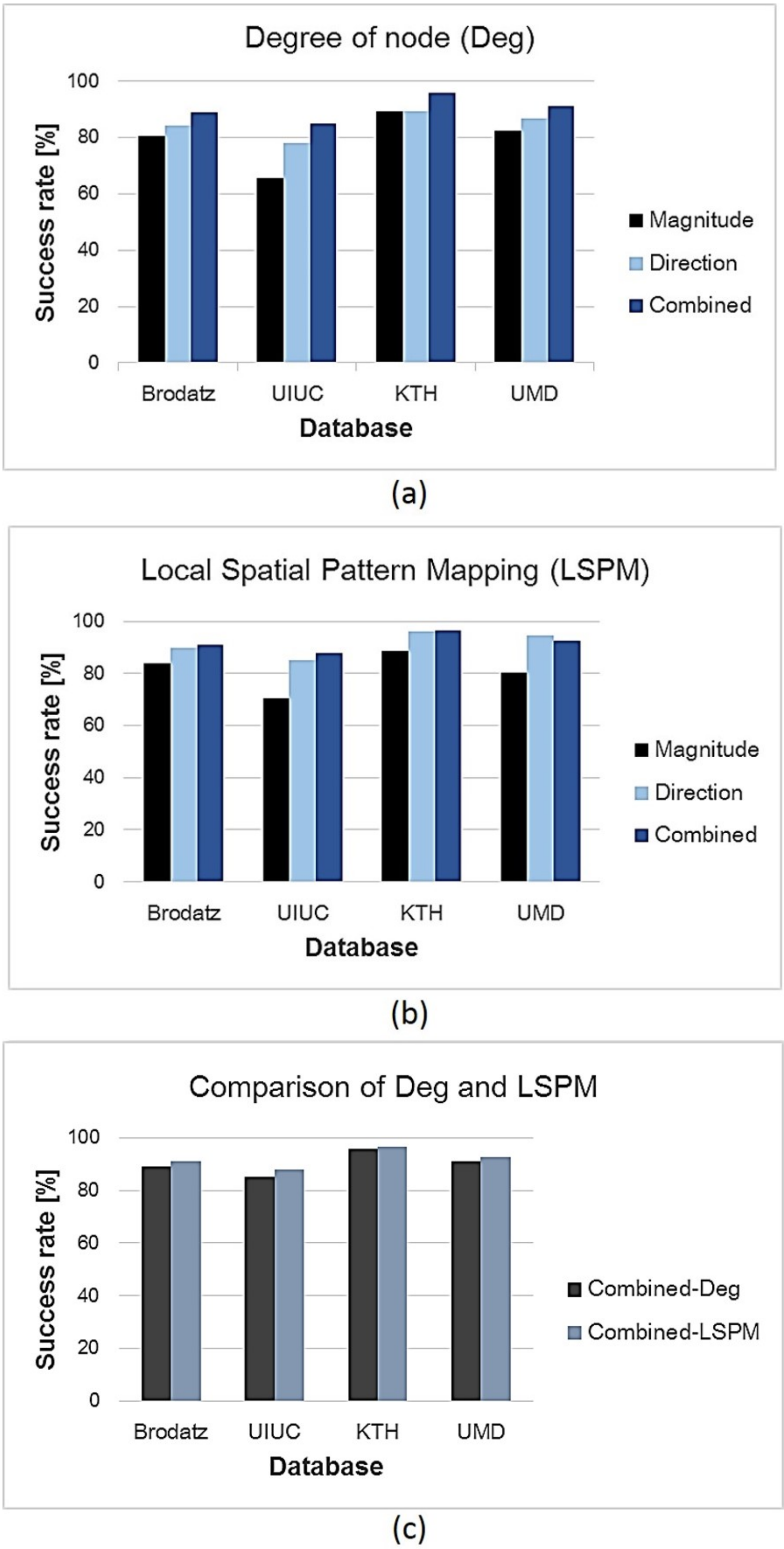


Figure 4.8: Summarized column chart results from Table 4.1 and Table 4.2

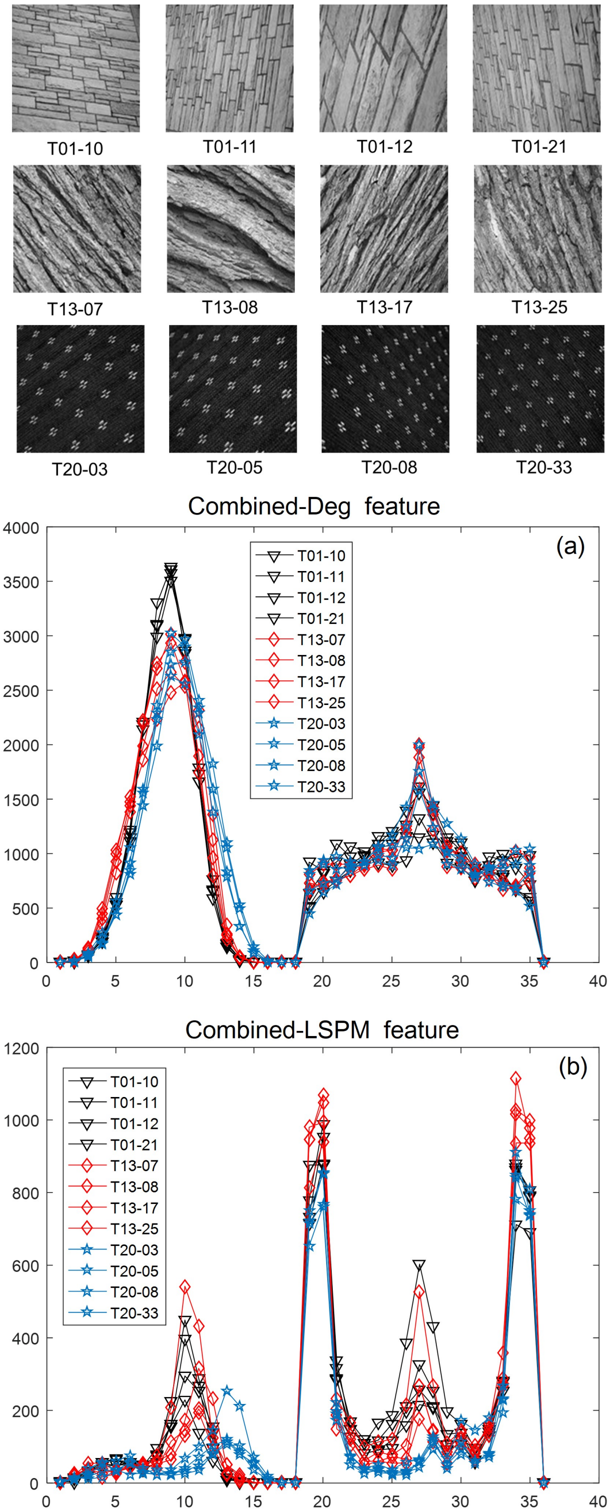


Figure 4.9: Histogram for three texture from the UIUC database. The bins 1 - 34 of the corresponding concatenate histograms from radial distance $r = 2 < d(v_{ij}, v_{i'j'}) \leq 3$.(a) The histogram is obtained by using Combined–Deg feature; (b)The histogram is obtained by using Combined–LSPM feature

Table 4.3: Success rate [%] when comparison with other texture analysis methods

Methods	Number of features	Success rate [%]			
		Brodatz	UIUC	KTH-TIPS	UMD
LBP	256	85.16 ± 15.70	66.53 ± 4.47	96.68 ± 0.59	92.96 ± 2.58
LBP^{riu2}	54	88.28 ± 13.34	82.21 ± 4.22	95.63 ± 0.56	94.52 ± 1.70
CLBP	648	86.77 ± 13.93	93.64 ± 2.50	97.20 ± 0.51	91.69 ± 1.94
CNTD	578	80.72 ± 15.80	70.44 ± 5.49	84.80 ± 1.29	90.10 ± 2.98
LSPM	578	88.13 ± 12.02	76.91 ± 4.78	89.27 ± 1.14	91.78 ± 2.87
CNTD–PCA	21	84.12 ± 13.38	75.42 ± 4.44	86.79 ± 1.08	92.72 ± 2.07
LSPM–PCA	21	86.28 ± 11.87	77.25 ± 4.35	89.38 ± 0.99	94.06 ± 2.13
Combined–Deg	68	89.13 ± 11.98	85.11 ± 2.86	95.98 ± 0.66	91.21 ± 2.85
Combined–LSPM	68	90.92 ± 12.02	87.92 ± 2.68	96.56 ± 0.49	92.65 ± 2.26

The considered methods are as follows:

- *LBP:* The LBP descriptor was computed by the concatenation of the histograms when (P, R) = (8,2) to characterize a texture pattern, a total of 256 descriptors.
- *LBP^{riu2} operators:* The LBP^{riu2} operators were chosen in this experiment [83,87] In the experiment, LBP^{riu2} descriptor was computed by the concatenation of the histograms when (P, R) = (8,1), (16,2), (24,3) to characterize a texture pattern, a total of 54 descriptors.
- *CLBP:* This scheme method [49] is used by the different local sign-magnitude to build CLBP_C, CLBP_S, and CLBP_M operators. In the experiments, the joint 3D histogram was employed to obtain CLBP_S/M/C. We used (P, R) = (16,2) with $riu2$ mapping, totaling 648 descriptors.

Table 4.3 has shown the success rate of the proposed method and other texture analysis methods from Brodatz, UIUC, KTH-TIPS and UMD databases. The combined descriptor results of Deg and LSPM methods in Table 4.1 and 4.2 are selected as the proposed descriptors for comparing with other methods. As the results, the combined descriptors that proposed in this Chapter are outperformed the proposed approaches in the Chapter 3, significantly. For Brodatz database, the results have shown Combined–LSPM descriptor obtained the highest classification rate of 90.92%, while the Combined–Deg obtained similarity the classification rate of 89.13%. For the challenging UIUC, the proposed descriptors results were more efficient than the others operators. These results confirmed the proposed approaches have efficiency for challenging environments (i.e., scale changed, uncontrolled environment, illumination changed) in texture classification task. Fig. 4.9 demonstrated the histogram from UIUC database by plotting the feature vector for four samples. These examples are challenging since they were acquired from different viewpoints. We can see from the plot that the histograms of each texture class are similar which corroborates the robustness under changes in viewpoints, in the same way in Deg and LSPM descriptors. Although the CLBP achieved the highest success rate on the UIUC database, this method required a high number of descriptors, whereas the proposed method is small. Therefore, the local discriminative information is beneficial information which can be extracted by the proposed approaches. For KTH-TIPS database, a success rate of 96.56% is achieved by the Combined–LSPM, which followed by a success rate of 95.98% is obtained by the Combined–Deg. On the other hands, the highest success rate of 97.20% is achieved by CLBP operator. For UMD database, a success rate of 94.52% is achieved by LBP^{riu2} operator, which followed by a success rate of 94.06% by the LSPM–PCA, the previous approach. The Combined-Deg and LSPM methods reached to 91.21% and 92.65%, respectively.

4.7 Application to clothing images

4.7.1 Motivation

Clothes can be defined as a deformable and a non-rigid object which is difficult for classifying an item when clothes are crumpled in a pile of laundry. This task is extremely challenging because clothing in free configuration can be highly wrinkled, tangled and in a huge variation in poses. Therefore, it is difficult to encode the clothing category into generic visual representation. Fig. 4.10 shows an example of clothing when lying on a table which has variation in poses with a textured surface.

To overcome the above challenge, an efficient feature descriptor still requires in this research area. Appearance information of clothes images have been used for developing feature descriptors for clothing classification [5, 13, 64, 112]. For instance, Yamazaki et al. [64, 112] have proposed clothing classification system by using fabrics, wrinkles and

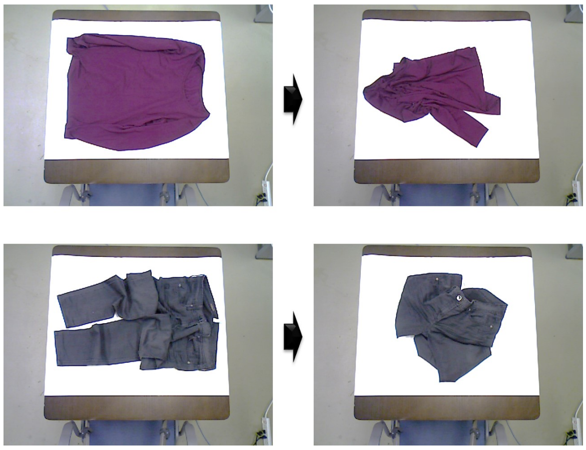


Figure 4.10: An example of clothes which lying on a table with pose variations and deformation of textured surface

cloth overlaps as features combining global and local information to derive input information [5,13]. The results of a combined local feature of global characteristic achieved high performance of classification. Accordingly, the wrinkle of fabric characterization can be used as a visual information which can be directly related to the object's surface. These works inspired us to develop the feature descriptor for seeking the unique feature on the surface fabrics, for example, texture patterns. However, it remains challenging to investigate the feature-enriched representation due to the natural texture characterization of fabrics can be presented by random and persistent stochastic patterns [14].

Capturing texture feature is an efficient way in order to represent the appearance of an object in an image. Textural information can provide an important information for object identification based on physical characteristics. Therefore, texture analysis research has greatly advanced for enhancing the texture pattern descriptors. In the recent years, image representation by graph theory has been employed for texture analysis [16]. Graph-based representation [80] is able to express the context surrounding of each pixel, and the relation among structural texture elements which is a crucial feature property used to distinguish a different class of image. Although the graph-based representation is effective for texture analysis and classification, there are various challenging issues which should be investigated for clothing category classification.

This paper proposes texture-based features for clothing category classification based on graph representation. The advantage of rotation uniformity of LBP mapping and

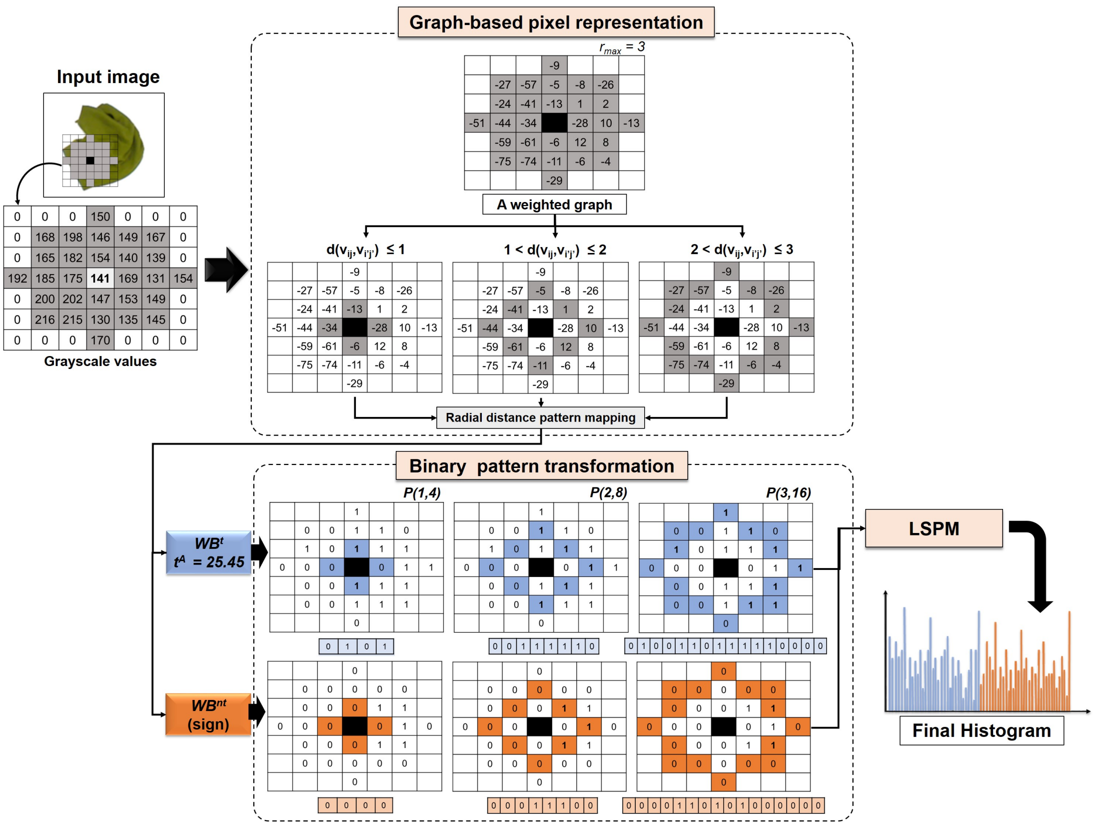


Figure 4.11: Overview the proposed approach using texture-based features via graph-based representation

graph theory is adopted to construct the feature descriptor. Therefore, the empirical synergy between LBP and graph theory is a promising direction in this work. The graph-based theory [80] is applied to represent the spatial relation of image pixels and their neighbors. The proposed network measurement in section **??**, local spatial pattern mapping (LSPM) is employed to encode the spatial arrangement of local spatial distribution. A clothing database and standard texture databases, Brodatz [24], and UIUC [70] are used for evaluation. The experimental results show the effectiveness of the proposed method compared to texture analysis based on conventional methods by the success rate of classification.

4.7.2 Proposed method

This section includes graph-based pixel representation and binary pattern transformation. Fig. 4.11 shows an overview of our proposed approach for clothing classification. The system can be separated into two parts. The first part illustrates the process of the graph-based pixel representation which including the deterministic of weighted graph and the radial distance pattern mapping. The weighted graph is defined by local grayscale difference. For the radial distance mapping which constructs by using the Euclidean distance between a node and pairwise connection. We have set radial distance r_{max} equal to 1, 2 and 3 as fixed window mapping with multi-scale of the neighborhood. The second part is the binary pattern transformation. The Fig. 4.11 illustrates the proposed approach using texture-based feature for clothing classification. The process is included in the two processes, deterministic weighted graphs, and binary pattern transformation as we explain in Section 4.3. The deterministic weighted graph can be applied for extracting local textural information which is included in the weighted-binary thresholding in Eq. 4.4 and the weighted-binary non-thresholding in Eq. 4.5. Feature descriptors are derived by using $riu2$ mapping technique [4], which the final histogram features are concatenated histograms from pattern_1, pattern_2, and pattern_3 as defined in Eq. 4.17.

4.7.3 Results and discussions

In all experiments, the nearest neighborhood with Euclidean distance has been used as a discrimination function, following by 10-fold cross-validations for discrimination performance. The simple classifier, for example, the nearest neighborhood was chosen rather than a more sophisticated classifier in order to demonstrate the importance of the features in the classification task. The experimental results can be separated into the results of the proposed approach in clothing dataset and in texture databases.

In the experiments, two standard texture databases and clothing dataset are used for evaluation as follows:

- Clothing dataset: The sample images were captured by using Asus Xtion PRO camera with controlled environment, for example illumination and scale. The resolution of an image was 640 $\times$ 480 pixels. The scale distances between a camera and a cloth was 900 [mm]. The databases include 4 categories, towel,

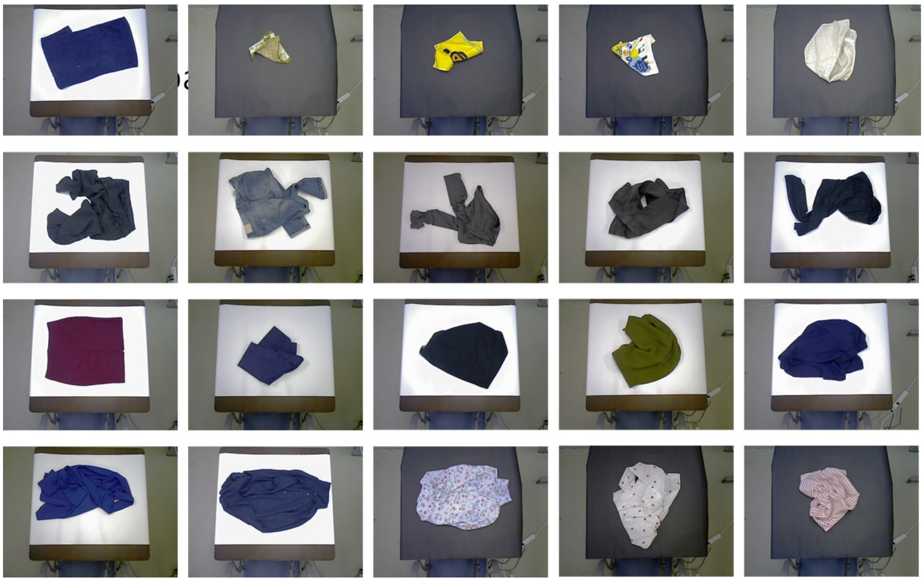


Figure 4.12: Example images from our clothing dataset which including towel, pant, skirt, and shirt.

shirt, pant, and skirt. In each category consist of 5 styles of clothing (see Fig. 4.12 for examples). This dataset contained 1000 images that including 50 images per style, 250 images per category. All databases were captured from each piece of clothing by throwing it randomly. Therefore, there were pose variations and deformation of the textured surface such as crumpled and smoothed that also made it challenging databases. Moreover, these clothes datasets have a large intra-class variation. Note that the color information was not used in the following experiment, because only grayscale images are used.

- Brodatz Texture Album: [24] is used in texture analysis and is a benchmark for evaluating methods. These data arranged in 100 classes, each class containing 10 grayscale samples of 128×128 pixels obtained by splitting the data of each class into 10 non-overlapping sub-images.

- UIUC database: This is a very challenging database [70]. The images have significantly different viewpoints and scales due to perspective distortion and non-rigid transformation. The image size is 128×128 pixels. For each of 25 classes, 40 grayscale images were considered in the experiments.

4.7.3.1 The proposed feature descriptor results in clothing dataset

The experimental results are shown as the confusion matrices results using the proposed feature and other comparison features which included Feature descriptor [12], Gabor filter [55], LBP, LBP^{riu2} [83, 87], and CLBP [49] features as illustrated in Fig. 4.13. In this figure, diagonal values indicate the success rate of each clothing class. Rows correspond to the true class, and column represents the predicted class. As the results, the proposed feature achieve a relatively stable performance among all categories or classes. In the proposed feature in pant, category achieved the highest success rate of 76.08%, while other methods were less than 67%. The worst result was obtained by the LBP feature with a success rate of 39.72%. From author aspect, the configuration of shirts and pants are more susceptible of being textured and crumpled. This likely leads to higher inter-class similarities.

The weighted-binary thresholding and non-thresholding have proposed for extracting local textural information in a different property. It should be noted that by combining (WB^t, WB^{nt}) properties in the deterministic weighted graph performs better than the separating the WB^t or WB^{nt}. To achieve high local discrimination capability, the local grayscale difference discriminative information in terms of WB^t and the local textural distribution by adopting rotation invariant micro-structure in terms of WB^{nt}, were proposed to distinguish difference local structures information in this paper. Although the clothing dataset is of high intra-class variation, the experimental results of the proposed feature are shown to be effective in extracting local discriminative information as texture-based features for clothing classification when compared with other feature methods.

4.7.3.2 The proposed feature descriptor results in texture databases

Table 4.4 is listed the success rate [%] of the proposed approach and other texture analysis methods using the Brodatz, UIUC, and clothing dataset. The Brodatz database results are shown that our proposed method achieved the highest success rate of 90.92% in texture Brodatz dataset. This result informed us about the combined local grayscale distribution and the second-order local structure information in the deterministic weighted graph can perform very well in local discrimination capability. UIUC database is a challenging database which includes sample images of material content

TP/FP(%)	Towel	Skirt	Shirt	Pant
Towel	25.68	36.08	26.84	11.4
Skirt	14.16	57.36	17.76	10.72
Shirt	10.96	15.32	44.8	28.92
Pant	4.36	2.96	26.44	66.24

Fourier descriptor feature

TP/FP(%)	Towel	Skirt	Shirt	Pant
Towel	96.08	1.04	2.8	0.08
Skirt	7.24	66.68	12.04	14.04
Shirt	3.76	6.48	80.88	8.88
Pant	0.44	12.24	20.36	66.96

Gabor filter feature

TP/FP(%)	Towel	Skirt	Shirt	Pant
Towel	94	3.8	1.32	0.88
Skirt	12.6	75.52	7.04	4.84
Shirt	7.08	13.32	65.84	13.76
Pant	9.32	19.2	31.76	39.72

LBP feature

TP/FP(%)	Towel	Skirt	Shirt	Pant
Towel	93.8	2.04	1.96	2.2
Skirt	9.28	72.24	6.64	11.84
Shirt	2.76	4.8	75.44	17
Pant	3.96	7.56	28.32	60.16

LBP^{riu2} feature

TP/FP(%)	Towel	Skirt	Shirt	Pant
Towel	98.84	0	0.76	0.4
Skirt	22.96	66.92	3.72	6.4
Shirt	17.16	3.32	68.24	11.28
Pant	17.8	4.04	12.64	65.52

CLBP feature

TP/FP(%)	Towel	Skirt	Shirt	Pant
Towel	95.68	1.6	1.08	1.64
Skirt	10.44	76.56	7.48	5.52
Shirt	4	3.8	72.6	19.6
Pant	3.48	7.36	13.08	76.08

The proposed feature

Figure 4.13: Confusion matrices for multi-class classification. In this figure, the class labels 1-4 corresponding to 'towel', 'skirt', 'shirt' and 'pant'.

Table 4.4: Comparison of the proposed method with other texture analysis methods

Method	No. features	Success rate [%]		
		Brodatz	UIUC	Clothing dataset
Fourier Descriptor	64	73.65	75.84	48.65
Gabor filter	40	58.29	50.24	77.69
LBP	256	85.16	66.53	68.82
LBP^{riu2}	34	89.43	84.97	75.05
CLBP	648	86.77	93.64	74.90
Combined-LSPM (Proposed)	68	90.92	87.92	81.60

with strong scale, rotation-viewpoint changes, and non-rigid deformation. The experimental results are shown that Completed LBP (CLBP) method achieved the best success rate of 93.64%, following the proposed method with a success rate of 87.92 %. As the number of the feature are listed in Table 4.4, we can see that the CLBP can extract more discriminative information than the proposed method based on the number of features. Moreover, the LBP^{riu2} can also achieve good result which is comparable with the proposed method. This experimental result can notice us that the UIUC database is affected by local grayscale different information. On the other hand, the proposed method achieved almost 88% which is comparable with other methods. Accordingly, these experimental results confirmed that the proposed feature descriptor is effective for describing the texture pattern on image textures and the clothing category classification.

4.8 Summary

In this Chapter, we propose a method for extracting the local sufficient discriminative information from the deterministic weighted graph which aids in texture classification. The radial graph represents image pixels with multiple radial distance patterns which applied for generating different feature vectors for texture analysis. The connected-weight graph based on magnitude and direction property approached for seeking more local discriminative information. Four standard texture databases, Brodatz, UIUC, KTH-TIPS, and UMD, are used for evaluation. The experimental results show the effectiveness of the proposed method compared to other methods, including the results in Chapter 3 in terms of the accuracy of classification. Moreover, clothing databases which includes deformable objects are used to evaluate the proposed method. Accordingly, the completed local textural information by decomposing the local image difference, i.e., the sign and the magnitude, can improve the capability of texture classification.

Chapter 5

Hybrid-based Complex Network Model

5.1 Introduction

Texture can represent the appearance of visual information such as the surface of an object or image. Different methodologies have been proposed for analyzing features from an image. Texture analysis based on complex network model has been investigated and studied in this research. These methods perform in spatial domain which is based on directly modifying the value of the pixels. Therefore, it is required to develop and formulate a robust description of intensity values in the neighborhood pixels of an image. Chapter 3 proposed a feature descriptor for enhancing the graph connectivity measurement by employing the local spatial pattern mapping (LSPM) through the original complex network model. The experimental results have shown the effectiveness in the proposed method when compared with original complex network model and other texture analysis methods. This work can let us know that to develop the model, the vertex measurement is important to describe meaningful texture information and has great effect to the system. In this case, we can explain uniformity and non-uniformity by pattern mapping which was inspired by $riu2$ mapping for describing the topology graph which obtained from dynamic network connectivity by applying a set of threshold. Chapter 4 is focused on the deterministic graph modeling. After we generated the weighted graph, we can extract more informative feature based on neighborhood pixels of an image. This work was inspired by the completed local binary pattern mapping

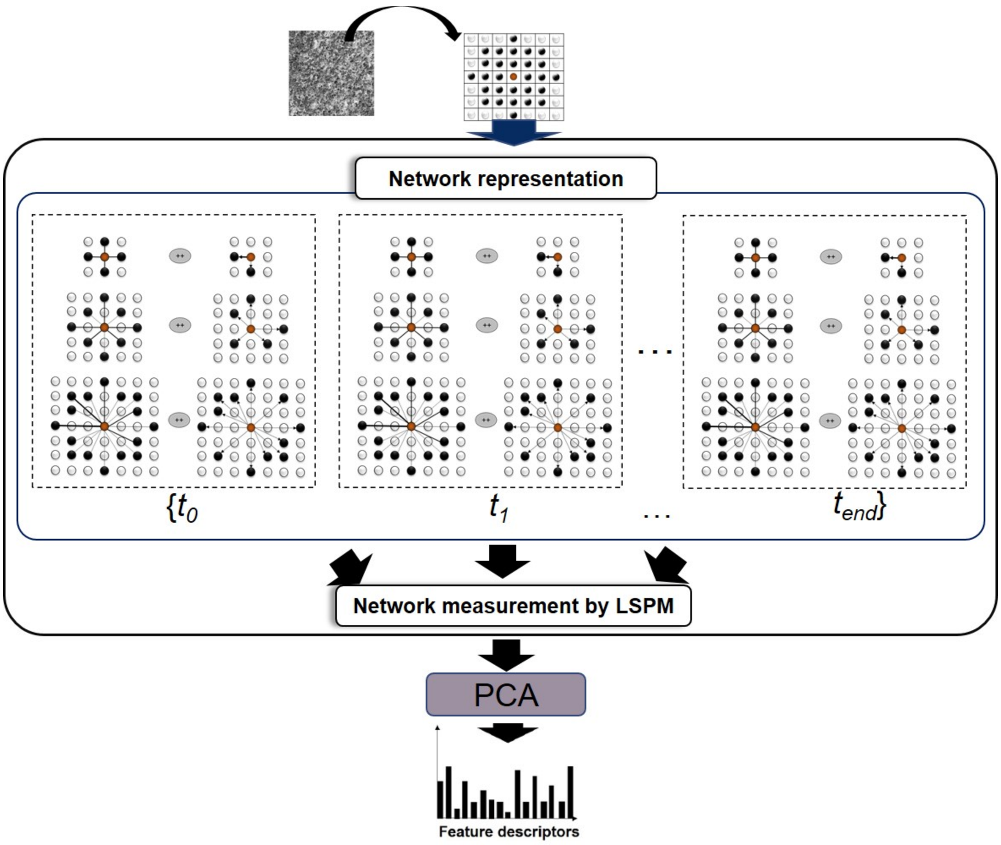


Figure 5.1: Structure of Overview model.

(CLBP) [49]. Images are represented by using graph theory as the concept of the complex network model. However, the dynamic network connectivity does not apply to analyze in this Chapter. Therefore, we can completely analyze relevant information in the neighborhood pixels of the image. The experimental results have shown that the deterministic modeling of the graph based on the neighborhood pixels of the image has effective to improve the classification performance when comparing with other methods.

According to these experimental results, this chapter presents the hybrid complex-network based approach for texture classification. This proposed model can describe discriminative information of textural pattern based on complex network model by combining the conceptual models of the Chapter 3 and Chapter 4 for the purpose of the classification task. Fig. 5.1 shows structure overview of the proposed method. More specially, as it is shown in Fig. 5.1, the topology graph is used to capture local discriminative information along with dynamic network connectivity. To verify the performance of this proposed method, standard texture databases are used for evaluation. Experimental results show that the proposed approach achieved outperformed accuracy when comparing with the performance classification in Chapter 3 also which advances the original complex network model [16] all databases. To summarize, the main contributions of this chapter can be described as follows:

1. A hybrid-based complex network model by spatial texture analysis is devised with increased performance for enhancing the original complex network model;

2. A deterministic network structure is developed with extracted local discriminative information reaching a high capability based on the complex network model;

3. The proposed model achieved the best result in large intra-class changes, including random rotation, large viewpoint variation, and largescale changes from UMD database.

The rest of this chapter is organized as follows: The architecture of the proposed approach is introduced in Section 5.2. The experiments and texture databases are presented in Section 5.3. Results and discussion in our proposed model are detailed in Section 5.4 and finally, the summarized of our proposed approach is described in Section 5.5.

5.2 Proposed approach

Fig. 5.1 illustrated scheme idea of the proposed approach. The proposed approach can be separated into two parts, the deterministic graph representation by a local difference direction-magnitude transform, and the graph connectivity measurement. A set of threshold t has been applied for generating dynamic network connectivity. After that, the graph connectivity measurement, spatial arrangement by the LSPM and the degree of node are used for characterizing the topology of graphs. In this section, we will explain the weight of edges and binary pattern transformation process. Then, the Principal component analysis (PCA) is employed for reducing dimensional data in this approach.

5.2.1 Weight of edges

This chapter represents the deterministic of the weighted of edges by different ways to investigate the importance of the weight of edges which can be used to represent local image textures. For each non-directed edge $e \in E$, we associate a weight $W(e)$, which is defined by the difference of intensity between a pixel $I(i, j)$ and its neighbors when $d(v_{ij}, v_{i'j'}) \leq r$. The weight of edges is given by:

$$W(e) = \begin{cases} I(i,j) - I(i^{'}, j^{'}) & \text{if } d(v_{ij}, v_{i'j'}) \leq r \\ 0 & \text{otherwise ,} \end{cases} \tag{5.1}$$

In this work, the weighted graph is transformed into a binary pattern for deriving context information about pixel surrounding. This approach enables us to analyze a local texture analysis. This transformation and graph properties are discussed in the following subsections.

5.2.2 Binary transformation

A threshold (t) is a parameter related to the property of being an edge in graph theory [36, 80]. In the original complex network model [16], a set of thresholds is used to construct a network that imitates dynamic transformation for the purpose of texture analysis as we demonstrated in the Chapter 3. In this study, threshold values obtained through an experiment. Then, the binary pattern transformation process is performed by converting the vertices whose weights are less than or equal to threshold t to 1, while the remaining vertices are converted to 0. This process is defined as follows:

$$W^t(e) = \begin{cases} W(e) & \text{if } |W(e)| \leq t \\ 0 & \text{otherwise ,} \end{cases} \tag{5.2}$$

where $W^t(e)$ represents the weight of edges whose weights are less than threshold t, while remaining pixels are converted to 0. Based on this equation 5.2, we can describe the local weight difference by decomposing the magnitude and the sign components, are given by:

$$WM_b(e) = \begin{cases} 1 & \text{if } W^t(e) \neq 0 \\ 0 & \text{otherwise .} \end{cases} \tag{5.3}$$

$$WD_b(e) = \begin{cases} 1 & \text{if } sign(W^t(e)) > 0 \\ 0 & \text{otherwise .} \end{cases} \tag{5.4}$$

These approaches are performed by converting the pixels to binary values. To define a threshold value, a set of threshold in Chapter 3 is used for the experiments in this chapter.

5.2.3 Feature descriptors

In this Chapter, the feature descriptors are generated by using the degree of node (Deg) and LSPM approach which are explained in this subsection.

5.2.3.1 Degree of Node (Deg)

The degree of a vertex v can be denoted $deg(v)$ which is the number of graph edges which incident to the vertex. We defined this $deg(v)$ of magnitude and direction properties as follows;

$$deg_m(v) = \sum_{e \in E} WM_b(e), \tag{5.5}$$

$$deg_d(v) = \sum_{e \in E} WD_b(e). \tag{5.6}$$

Based on multiple scale analysis, we have set radial distance $r_{max} = 3$ in the experiment, we concatenate histograms for different value of threshold t, is given by:

$$G_M^r(v) = [deg_m^{r,t_0}(v), deg_m^{r,t_1}(v), \ldots, deg_m^{r,t_{final}}(v)] \tag{5.7}$$

$$G_D^r(v) = [deg_d^{r,t_0}(v), deg_d^{r,t_1}(v), \ldots, deg_d^{r,t_{final}}(v)] \tag{5.8}$$

$$\delta = [H(G_M^{r_1}), H(G_M^{r_2}), H(G_M^{r_3})] \tag{5.9}$$

$$\theta = [H(G_D^{r_1}), H(G_D^{r_2}), H(G_D^{r_3})] \tag{5.10}$$

The final histograms of the hybrid complex network model based on the magnitude and the direction by using a degree of node, is given by:

$$\Theta = [\delta, \theta]. \tag{5.11}$$

5.2.3.2 Local Spatial Pattern Mapping

A spatial texture analysis is performed by local spatial pattern mapping or LSPM. The LSPM method is used to describe the uniformity of texture primitives when the binary pattern of a binary row record contains at most two bit-wise transitions between 0 and 1 in the same way as uniformity in LBP theory [83]. We define the LSPM method as follows:

$$lspm^m(e) = \sum_{n=1}^{v'} WM_b(e) 2^{(v'-1)}, \tag{5.12}$$

$$lspm^d(e) = \sum_{n=1}^{v'} WM_b(e) 2^{(v'-1)}, \tag{5.13}$$

where v' is number of neighbors. For considering the uniformity of $lspm$, the following equation is used:

$$\text{LSPM}^m(p_n, r_n) = \begin{cases} lspm^m(e) & \text{if } U(lspm^m(e)) \leq 2 \\ p+1 & \text{otherwise,} \end{cases} \tag{5.14}$$

$$\text{LSPM}^d(p_n, r_n) = \begin{cases} lspm^d(e) & \text{if } U(lspm^d(e)) \leq 2 \\ p+1 & \text{otherwise,} \end{cases} \tag{5.15}$$

where U is the uniform pattern of $WB^m(e)$ and $WB^d(e)$, which is determined when the binary pattern of a binary row record contains at most two bit-wise transitions between 0 and 1. For example, the pattern of 00000000 shows the U value of 0, whereas the binary pattern of 11000001 shows U equal to 2 as justified by [83]. This equation means that if the $lspm(e)$ have $U > 2$, it defines for non-uniform pattern. This step enables us to analyze the uniform pattern of pixel surroundings, which can refer to local texture analysis. In practice, LSPM is implemented by using a look-up table of 2^{p_n} elements. In this case, there are $p_n + 2$ output bits for each final histogram.

$$K_M^r(v) = [\text{LSPM}^{m,t_0}(p_n, r_n), \text{LSPM}^{m,t_1}(p_n, r_n), \ldots, \text{LSPM}^{m,t_{final}}(p_n, r_n)] \tag{5.16}$$

$$K_D^r(v) = [\text{LSPM}^{d,t_0}(p_n, r_n), \text{LSPM}^{d,t_1}(p_n, r_n), \ldots, \text{LSPM}^{d,t_{final}}(p_n, r_n)] \tag{5.17}$$

In this case, there are $p_n + 2$ output bits for each histogram. The feature properties as histogram for the radial analyses LSPM(p_n, r_n) are defined as follows:

$$\delta'' = [H(K_M^{r_1}), H(K_M^{r_2}), H(K_M^{r_3})] \tag{5.18}$$

$$\theta'' = [H(K_D^{r_1}), H(K_D^{r_2}), H(K_D^{r_3})] \tag{5.19}$$

The final histograms of the hybrid complex network model based on the magnitude and the direction by using a local binary pattern mapping (LSPM), is given by:

$$\Phi = [\delta'', \theta'']. \tag{5.20}$$

For comparing with other methods, Principal Component Analysis (PCA) is applied to downsize the feature space purpose [54] on the proposed methods. In order to determine optimal range number of principal components, we have set the percentage of the total variance explained by each principal component no more than 99.60%—99.70%, to obtain the optimal number of PCs. To evaluate our proposed method, a discrimination function for texture classification was generated by the nearest neighborhood. In the implementation of this work, the *Classification Learner* app of MATLAB 2016a version with default parameter values was used for classification following 10-fold cross-validation.

5.3 Experiments

In this Chapter, the experiments are followed by the Chapter 3. The first experiment was a comparison of different threshold sets as represented in Table 5.2 and Table 5.3. By applying PCA for reducing the feature spaces, the number of the descriptor are listed in Table 5.4.

The summarized databases are listed in Fig. 5.2. In this thesis, we built the new Brodatz dataset by cropping 12 subsections with non-overlapping of a larger Brodatz image. Thus, some image is difficult to distinguish between each class. The last experiment was a comparison with other conventional methods and included Fourier descriptor, Gray-occurrence matrices, Gabor filter, LBP, LBP$^{\mathrm{riu2}}$, CLBP. Moreover, the results from the Chapter 3, Chapter 4 and Chapter 5 are chosen to compare the results in Table 5.5.

Databases	Resolution	Classes	#images in Total	Description
Brodatz	128x128	100 classes, 12 images per class	1200	Lack of intra-class variations
UIUC	128x128	25 classes, 40 images per class	1000	Strong scale, rotation and viewpoint changes, non-rigid deformation, material contents
KTH-TIPS	128x128	10 classes, 81 images per class	810	Illumination changes, mall rotation changes, large scale changes
UMD	128x128	25 classes, 40 images per class	1000	Strong scale, rotation and viewpoint changes, object contents

Figure 5.2: Summary of various properties of important texture databases

Table 5.1: The configuration threshold sets that which are applied in the experiments.

Set	Thresholds		
	t_0	t_{step}	t_{final}
T1	5	5	85
T4	5	10	85
T7	5	15	80

5.4 Results and discussions

5.4.1 Comparison of results from different threshold sets

The best threshold sets were selected regarding the experiments in the Chapter 3 for comparison which included the configurations $T1, T4$and $T7$ as listed in Table 5.1. The experimental results of a different configuration threshold are given in Table 5.2 for the Hybrid–LSPM approach, whereas the Hybrid–Deg is shown in Table 5.3. As results, the classification rates of each set of threshold achieved similarity accurate classification rates in all databases. The average success rate results are summarized as column chart in Fig 5.3. By using Deg and LSPM as a descriptor in this approach, the accurate classification rates are shown similarity achievement. These experiments show results which not in the same direction according to the results in Chapter 3 and 4. Although the Degree of node (Deg) is abandoning the local structural information as we

Table 5.2: Experimental results of Hybrid–LSPM feature for different a set of threshold on the four databases

Datasets	T1	T4	T7	Average
Brodatz	88.92 ± 11.77	87.10 ± 11.98	87.55 ± 11.55	87.86 ± 11.77
UIUC	85.46 ± 3.42	85.18 ± 3.49	85.59 ± 3.54	85.41 ± 3.48
KTH-TIPS	95.14 ± 0.70	94.98 ± 0.71	94.80 ± 0.74	94.97 ± 0.71
UMD	95.52 ± 1.74	95.45 ± 1.72	95.61 ± 1.82	95.53 ± 1.76

Table 5.3: Experimental results of Hybrid–Deg feature for different a set of threshold on the four databases

Datasets	T1	T4	T7	Average
Brodatz	87.98 ± 11.20	87.58 ± 11.36	87.50 ± 11.29	87.69 ± 11.29
UIUC	83.19 ± 3.95	83.09 ± 3.72	83.29 ± 3.80	83.19 ± 3.83
KTH-TIPS	95.07 ± 0.67	94.96 ± 0.70	94.98 ± 0.66	95.00 ± 0.68
UMD	95.85 ± 1.62	95.55 ± 1.77	94.66 ± 1.88	95.35 ± 1.75

discussed in Section 3.3.1, their performance when applied in the hybrid-based complex network is almost the same as the LSPM. Therefore, the Deg and LSPM descriptors in graph connectivity measurement do not mainly contribute to the process to increase the classification performance when we considered and compared the results in Chapter 3.

5.4.2 Comparison with other texture Analysis Methods

For further evaluate our proposed method, the additional conventional texture analysis methods are chosen for comparison which including, Fourier descriptor, Gray-occurrence matrices, Gabor filter, LBP, LBP^{riu2}, CLBP. Moreover, the results from the Chapter 3, Chapter 4 and Chapter 5 were chosen in this experiment. The considered methods are as follows:

- *Fourier descriptors:* The 2D Fourier transform was applied to each image following with the shifting operator for the resulting spectrum. The feature descriptor obtained by summing all the absolute values of the coefficients from the shifted spectrum at the same radial distance from the image center [12].

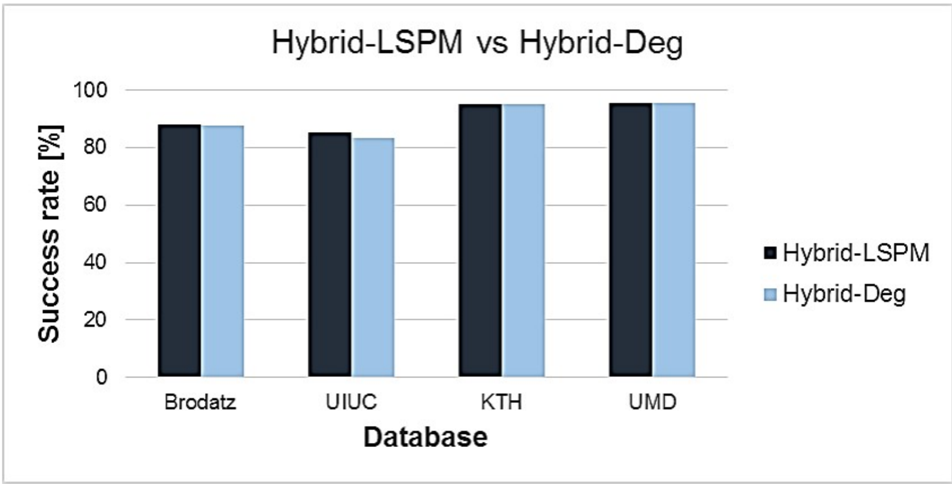


Figure 5.3: Summarize column chart results from Table 5.2 and Teble 5.3

- *Gabor filters:* This method provides the spatial localization difference frequency, and orientation by using a sinusoidal plane wave [55]. From the convolution of these filters over an input image, we used energy as a descriptor. A total of 40 filters (combinations of 8 rotation filters and 5 scale filters) and a frequency range from 1.2 to 1.4 were applied in this experiment.

- *Co-occurrence matrices:* Each matrix represents the joint probability of a pair of pixels which separated by determining distance d and direction θ. The co-occurrence matrix for $d = 1$ and 2 with angles $\theta = 0$, 45, 90, and 135, in a non-systemic version for each image were computed in this experiment. Energy and entropy descriptors were approached as feature descriptor from each co-occurrence matrix to compose an image feature vector [50].

- *LBP:* The LBP descriptor was computed by the concatenation of the histograms when $(P, R) = (8{,}2)$ to characterize a texture pattern, a total of 256 descriptors.

- *LBP^{riu2} operators:* The LBP^{riu2} operators were chosen in this experiment [83,87] In the experiment, LBP^{riu2} descriptor was computed by the concatenation of the histograms when $(P, R) = (8{,}1)$, $(16{,}2)$, $(24{,}3)$ to characterize a texture pattern, a total of 54 descriptors.

- *CLBP:* This scheme method [49] is used the different local sign-magnitude to build CLBP_C, CLBP_S, and CLBP_M operators. In the experiments, the joint 3D histogram was employed to obtain CLBP_S/M/C. We used (P, R) = (16,2) with $riu2$ mapping, totaling 648 descriptors.

Table 5.4: The number of feature by apply PCA approach in database

Method	Brodatz		UIUC		KTH-TIPS		UMD	
	D	Acc	D	Acc	D	Acc	D	Acc
Hybrid–LSPM	24	88.92 ± 11.77	37	85.46 ± 3.42	22	95.14 ± 0.70	21	95.52,± 1.74
Hybrid–Deg	29	87.98 ± 11.20	47	83.19 ± 3.96	27	95.07 ± 0.67	27	95.85 ± 1.62

Table 5.5: Success rate [%] when comparison with other texture analysis methods

Methods	Number of features	Success rate [%]			
		Brodatz	UIUC	KTH-TIPS	UMD
Fourier descriptors	64	74.45 ± 19.90	75.84 ± 3.90	89.48 ± 1.35	87.95 ± 3.16
Gray-occurrence matrices	24	79.68 ± 19.01	69.77 ± 5.27	80.00 ± 1.56	86.65 ± 3.66
Gabor filter	64	70.28 ± 21.06	59.90 ± 6.06	90.81 ± 0.88	81.32 ± 5.14
LBP	256	85.16 ± 15.70	66.53 ± 4.47	96.68 ± 0.59	92.96 ± 2.58
LBP^{riu2}	54	88.28 ± 13.34	82.21 ± 4.22	95.63 ± 0.56	94.52 ± 1.70
CLBP	648	86.77 ± 13.93	93.64 ± 2.50	97.20 ± 0.51	91.69 ± 1.94
CN–Deg	578	80.72 ± 15.80	70.44 ± 5.49	84.80 ± 1.29	90.10 ± 2.98
CN–LSPM	578	88.13 ± 12.02	76.91 ± 4.78	89.27 ± 1.14	91.78 ± 2.87
CN–Deg(PCA)	21	84.12 ± 13.38	75.42 ± 4.44	86.79 ± 1.08	92.72 ± 2.07
CN–LSPM(PCA)	21	86.28 ± 11.87	77.25 ± 4.35	89.38 ± 0.99	94.06 ± 2.13
Graph–Deg	68	89.13 ± 11.98	85.11 ± 2.86	95.98 ± 0.66	91.21 ± 2.85
Graph–LSPM	68	90.92 ± 12.02	87.92 ± 2.68	96.56 ± 0.49	92.65 ± 2.26
Hybrid–Deg		87.96 ± 11.20	83.19 ± 3.96	95.07 ± 0.67	95.85 ± 1.62
Hybird–LSPM		88.92 ± 11.77	85.46 ± 3.42	95.14 ± 0.70	95.52 ± 1.74

Table 5.5 shows the success rate of the proposed method and other texture analysis methods on Brodatz, UIUC, KTH-TIPS and UMD databases. The methods from the Chapter 3 proposed a new graph connectivity measurement based on complex network model (CN). Thus, the operators are denoted as CN–Deg, CN–LSPM, CN–Deg(PCA) and CN–LSPM(PCA), respectively. The methods from the Chapter 4 proposed a graph based image representation based spatial property. Therefore, the methods are denoted as Graph–Deg and Graph–LSPM. The results of Hybrid–LSPM and Hybrid–Deg

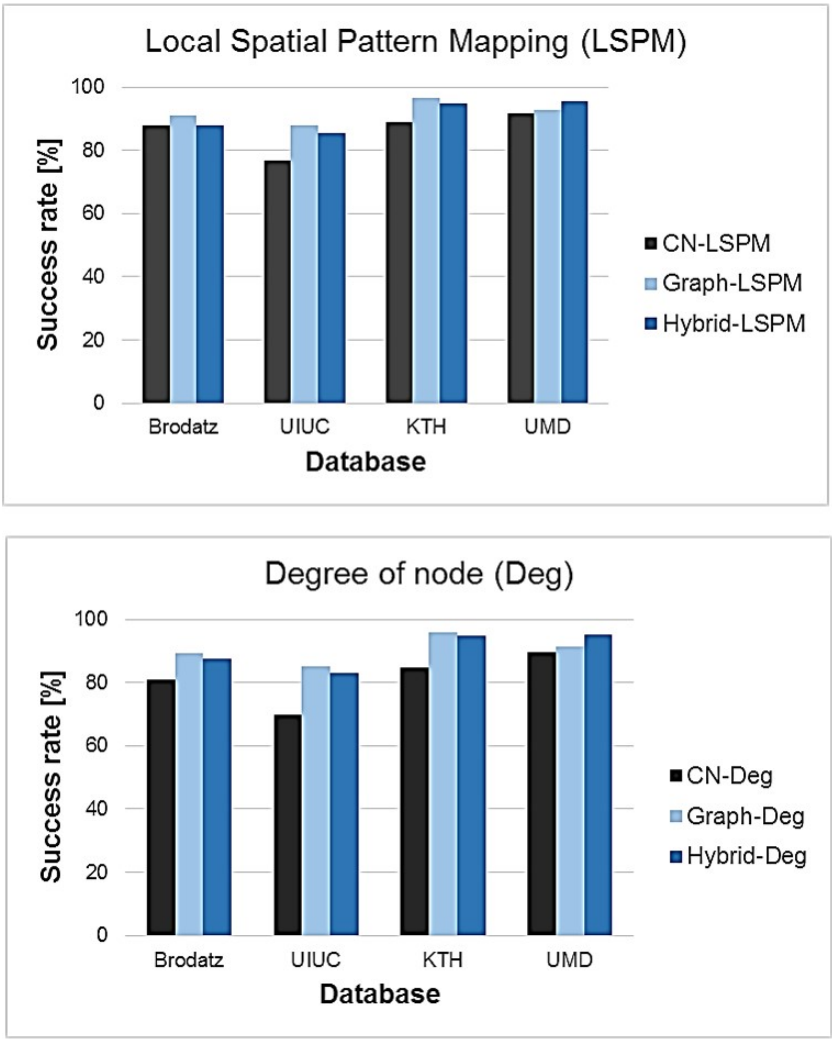


Figure 5.4: Summarize column chart results from Table 5.5

methods in Table 5.4 are selected as the proposed descriptors for comparing with other methods, following with a different number of features by applying PCA approach, respectively.

For Brodatz database, the results are shown Graph–LSPM descriptor obtained the highest classification rate of 90.92%, which following with accurate classification rate of 89.13% by Graph–Deg. On the other hand, the proposed approaches, Hybrid–LSPM and Hybrid-Deg achieved similarity correct classification rates of 88.92% and 87.92%, respectively. These accurate results are obtained as similar as the CN–LSPM method and LBP^{riu2} operator, 88.13%, and 88.28%, respectively. For the challenging UIUC, the Graph-based method, proposed in the Chapter 4 are more accurate than Hybrid-based method. Although the Hybrid-based approach result is not achieved the highest classification rate, these experimental results suggest that our method has good generalization capability. For KTH-TIPS database, the experimental results have shown that the Hybrid-based method, the Graph-based method and LBP operator are achieved similarity accurate classification rates in the database. Moreover, due to the results, we observed that all the success rates have outperformed the CN–Deg or proposed by CNTD [16] in a significant way. For UMD database, the experimental results are shown that the Hybrid-based methods, Hybrid–LSPM and Hybrid–Deg, achieved the highest accurate classification rate of 95.52% and 95.85% than other methods. These results could be informed us about how to contribute the hybrid-based approach is, by using the database category. The textures of this database are non-traditional, including an image of fruits, various plants, floor texture shelves of bottles and buckets. Moreover, this database has significant viewpoint changes and scale differences with uncontrolled illumination conditions.

5.4.3 Analysis on all proposed approaches

This section discusses and analyzes the results of our proposed methods in Chapter 3, 4, and 5. Fig. 5.4 has shown the summarize column chart from the results. In Chapter 3, we proposed the LSPM methods (CN–LSPM) for encoding local spatial structure which useful for texture discrimination. The results informed us about the LSPM can be employed as a new graph connectivity measurement. Although the local spatial structure has encoded in this method, the discriminative capability should be improved. Accordingly, the complementary features by local difference vector are adopted to characterize

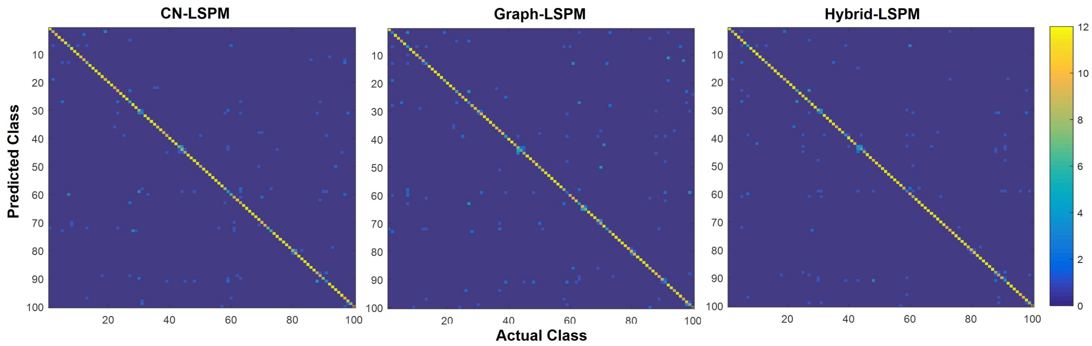


Figure 5.5: Confusion matrices comparison results on Brodatz database

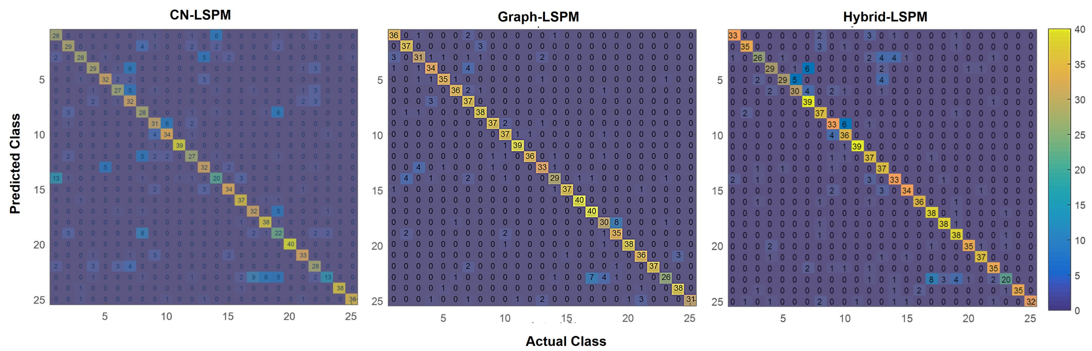


Figure 5.6: Confusion matrices comparison results on UIUC database

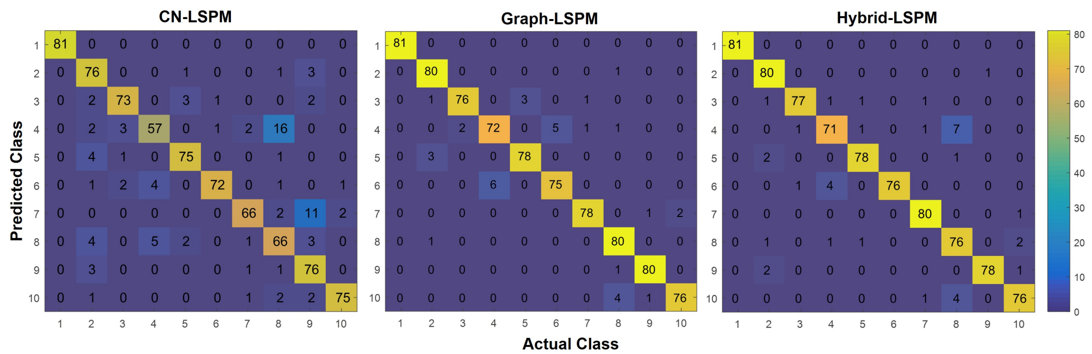


Figure 5.7: Confusion matrices comparison results on KTH-TIPS database

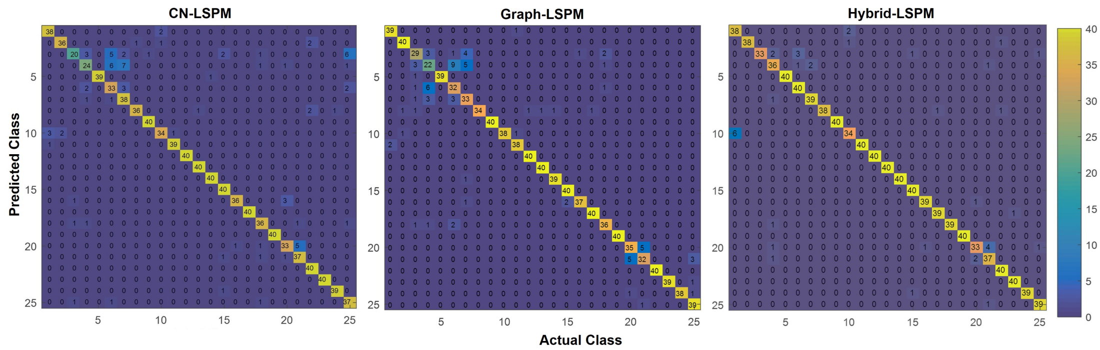


Figure 5.8: Confusion matrices comparison results on UMD database

the image local structure at the vertex and its neighbors in Chapter 4. We have devised the graph-based spatial vector properties (Graph–LSPM) which decomposed into two components; the connected-graph based on magnitude property (mag) and connected-graph based on direction property (sign). The experiment results showed the sign or direction component reached more accurately preserve information (more informative) than the magnitude component. However, the combined (fuse) two components, the magnitude and the direction components, showed they achieved better and more robust results than the results in Chapter 3. Fig. 5.4 demonstrated how accurate of this complementary features outperformed other methods in Brodatz, UIUC, KTH-TIPS databases. These mainly because of the local discriminative information that the Graph–LSPM proposed for rotation and scale invariance. However, in UMD database where included large-intraclass and affine variation, the performance of Graph–LSPM is not better than Hybrid–LSPM because of it has limited capability to address affine and viewpoint invariance. In Chapter 5, we proposed the hybrid-based complex network model (Hybrid–LSPM) for enhancement the original complex network model. This method noticed us about how the dynamic network transformation by a threshold configuration has influenced to the model, especially in UMD database.

In Fig. 5.8 illustrated the confusion matrices comparison results from UMD database. We can see the predicted classes in class 3-5 where CN-LSPM and Graph-LSPM do not achieve prediction correctly, whereas the Hybrid-LSPM does more discriminate against these classes. On the other hand, the CN–LSPM and Hybrid-LSPM methods achieved better results than Graph–LSPM. This is an important finding that a set of thresholds, which employed to express difference local graph structure can be used to address scale and may contribute additional discriminative information if it is properly used in affine invariances.

5.5 Summary

In this Chapter, we propose a hybrid-based method for enhancing the original complex network model. The radial graph represents image pixels with multiple radial distance patterns which are applied for generating different feature vectors for texture analysis. The connected-weight graph based on magnitude and direction property is integrated into the complex network model, following with the new graph connectivity measurement which we referred as LSPM. Four standard texture databases, Brodatz, UIUC, KTH-TIPS, and UMD, are used for evaluation. The experimental results show the effectiveness of the proposed method compared to the previously proposed methods and conventional texture analysis methods.

Chapter 6

Conclusions

6.1 Objectives and hypotheses revisited

In this chapter, the achievements are summarized, the initial hypotheses are reviewed, and the limitations are illustrated. The scientific results support the validation of the proposed hypotheses. At the same time that the boundaries of the proposed approaches are investigated, the potential solutions to address these limitations are discussed.

The objective of this thesis are: (1) To enhance the original complex network-based method for texture analysis through a spatial texture analysis; (2) To extract discriminative information through an enriched texture characterization which is invariant to uncontrolled environments [1]; (3) To integrate enhanced complex network model and enriched texture representation for texture characterization. Corresponding to the objectives, the hypotheses of this work are three-fold;

- In order to develop a new graph connectivity measurement, the spatial distribution of pixels must be considered among dynamic network connectivity in order to capture discriminative information which being used to distinguish various pattern structures. If the graph connectivity is measured by encoding the spatial arrangement of distribution of local pixels, then the local spatial structure information which is visual micro-structure (e.g., edge, line, spots) can be more detectable on local image texture. The encoding spatial arrangement is more robust than a degree of node connectivity for uncontrolled environment database.

[1] here, the uncontrolled environment includes scale orientation, viewpoint variation, and illumination changed

- In order to enhance a deterministic weight of graph, the weight of edge can be adapted for seeking more local discriminative information. If completed local textual information is obtained by decomposing the local image difference in terms of directions and magnitudes, topology if the graph can be generated and the capability of texture classification can be improved.
- The efficacy in discrimination of the original complex network model can be improved from uncontrolled environment databases if integrating between the new graph connectivity measurement and the enriched as graph representation is proposed. The completed local textural information from the graph representation is more robust than the local structure information from the new graph connectivity measurement under uncontrolled environment database.

From work reported in previous chapters, the objectives have been achieved, and the hypotheses have been validated. More details are illustrated in the following subsections.

6.2 Summary of contributions

This section summarized the achievements of this thesis in three phases: (1) enhancing complex network-based for texture characterization, (2) graph connectivity measurement, and (3) spatial vector-based graph representation.

6.2.1 Enhancing complex network-based for texture characterization

The major contribution of this thesis is to enhance complex network-based model for texture characterization via spatial texture analysis. In the existing literature about complex network model for texture analysis, the proposed model is the only one which has been presented and demonstrated in pattern recognition perspective, opened new or relevant research area in computer vision. This model contains two parts: the encoding spatial arrangement part for the graph connectivity measurement, and the deterministic graph part through the spatial vector-based graph representation. On the one hand, the proposed enhanced complex network-based model can contribute to robust texture descriptor by encoding the spatial arrangement of distribution of local pixels for an uncontrolled environment. On the other hand, the enriched deterministic of the weighted graph obtained by decomposing the magnitude and the direction, which is a spatial vector property, is invariant to scale different, and rotation variation. This invariant enriched deterministic graph modeling is integrated into the enhancing complex network model for texture classification and achieves a substantial advancement on the traditional model.

6.2.2 Graph connectivity measurement

This thesis presents a new network or graph connectivity measurement which denoted as a local binary pattern mapping (LSPM) descriptor that is adaptable of binary pattern mapping for encoding local spatial structure information in order to describe various the microstructure pattern. In this proposed pipeline, the original complex network model is advanced in discrimination capability. To be specific, instead of using a degree of node, which distinguish different distribution of local pixel by statistic of number of connectivity of a vertex in the graph, this thesis proposes the local spatial pattern mapping (LSPM) descriptor in order to measure graph connectivity which shows the effectiveness in the discrimination capability and rotation invariance.

The evaluations of the graph connectivity measurement include two parts: In Chapter 3, the performance of the proposed graph connectivity measurement by LSPM approach is compared with the traditional complex network model, which is denoted by CNTD, and other texture analysis methods by using four standard texture databases, Brodatz, UIUC, KTH-TIPS and UMD databases. The proposed graph connectivity measurement outperforms the traditional complex network model in terms of classification rate performance from invariant to environment and discriminative capability perspective. This is because the proposed descriptor encoding local structure information in various micro-structure on image texture, which achieves 88.13% accuracy on Brodatz, a benchmark texture database, outperforming the traditional by 7.41%, and 76.91% UIUC, challenging database that significantly viewpoint changes and scale difference, outperforming the traditional by 6.44%. In Chapter 4, the proposed graph connectivity measurement is employed in graph-based spatial property analysis in order to investigate the contribution of the enriched deterministic graph representation. In the experimental results shows that the enriched graph-based image representation integrated with the new graph connectivity measurement improves the enriched graph-based image representation. (success rates of +0.87%, +2.81%, +0.58%, and +1.44% in the enriched graph-based representation with the proposed (LSPM) approach, compared with the enriched graph-based representation with a degree of node (Deg) approach,in Brodatz, UIUC, KTH-TIPS and UMD, respectively.

6.2.3 Spatial vector-based graph representation

In Chapter 4, part of graph-based image representation is proposed and applied to a hybrid-based complex network for texture analysis in Chapter 5. The task is to extract local discriminative information through the deterministic a weight of edge in order to improve a capability of texture classification. This graph representation adapts a spatial vector property that has magnitude and direction for seeking relevant information based on local image difference. This representation is robust to the uncontrolled environment; scale changed, viewpoint variation and rotation. The experimental validations include the same four standard texture databases as all the proposed approaches in this thesis.
The evaluations of the spatial vector-based graph representation include two parts: In Chapter 4, the model is denoted as a combined method, the magnitude, and the signs, in order to create a topology graph. Then, the proposed graph connectivity measurement (LSPM) and the degree of node (Deg) are applied for evaluation of the model. The experimental results show that combined–LSPM descriptor outperforms the combined–Deg descriptor. Moreover, the proposed graph-based image representation achieves outperforms the traditional complex network model and the proposed approach in Chapter 3. This substantial improvement can be attributed to the more advanced the traditional complex network and the more robust the deterministic a graph for generating the weighted graph which is part of complex network-based model for texture analysis. In the second validation, the integrated this spatial vector-based graph representation with the proposed graph connectivity measurement in Chapter 5 in order to investigate the contribution of the hybrid-based complex network. The experimental results achieve a reasonable performance with texture classification task, compared with the original complex network model.

6.2.4 Summary

This thesis proposes an enhancing complex network-based model for texture classification via spatial texture analysis. The proposed enhancement model can be comprised of into two parts: The topology of graph part is devised graph-based image representation and the deterministic graph for seeking more local discriminative information which approaches in classification task; the graph connectivity measurement part is to encode spatial distribution of pixel and its neighbors that are robust to uncontrolled environment. Employing the enriched deterministic graph for generating topology graph and the encoding spatial arrangement approach in graph connectivity measurement can be enhanced in the traditional complex network-based model for texture classification.

6.3 The validation of hypotheses

From the achievements presented in this thesis, the pre-proposed hypotheses can be validated which is discussed in this section.

The first hypothesis of this thesis is:

- In order to develop a new graph connectivity measurement, the spatial distribution of pixels must be considered among dynamic network connectivity in order to capture beneficial information being used to distinguish various pattern structures. If the graph connectivity is measured by encoding the spatial arrangement of distribution of local pixels, then the spatial structure information which is visual micro-structure (e.g., edge, line, spots) can be more detected on local image texture. The encoding spatial arrangement is more robust than a degree of node connectivity for uncontrolled environment database.

In this thesis, sufficient discriminative information and feature extraction aim to enhance the traditional complex network-based model. As it is reported in Chapter 3, an accurate local spatial pattern mapping (LSPM) descriptor (part of the proposed enhancing complex network-based model) outperforms a degree of node (Deg) method, which can distinguish different distribution of local pixel by statistic of number of connectivity of a vertex in the graph, in texture classification, especially in database with significantly scale changed and viewpoint variation. This demonstrates that an encoding spatial arrangement can be used for seeking sufficient discriminative information than that by a degree of node. To develop a robustness graph connectivity measurement is a solution for enhancing the traditional complex network model in the classification task. In Chapter 4, the proposed graph connectivity measurement is employed to describe the graph-based spatial property representation. The experimental results prove that more discriminative information of texture can be acquired by an enriched graph connectivity measurement, thereby improving the performance of the classification rate. Besides, the local structure information of texture which is visual micro-structure is also investigated based on the proposed approach.

The second hypothesis of this thesis is:

- In order to enhance a deterministic of a weighted graph, the weight of edge can be adapted for seeking more local discriminative information. If a completed local textural information by decomposing the local image difference, i.e., the signs and the magnitude, is applied for generating a topology of the graph, then the model can improve a capability of texture classification.

Instead of describing the texture pattern by applying a set of threshold in order to obtain additional insights the properties of the network, this thesis proposed a more additional discriminative information which enhances a deterministic a wight of edge by decomposing the image local differences into the spatial vector property. This proposed enhancement demonstrates its robustness in terms of the improvement in classification rates. To be more specific, in Chapter 4, the enhancement graph-based spatial properties approach is presented. This is an enriched topology graph representation incorporating the magnitude and the direction based on the spatial vector. This proposed method is applied to four texture databases. From the comparison experiments, the proposed enhancement the deterministic of graph approach outperforms the proposed method in Chapter 3, and the traditional complex network model (CNTD) [16]. This deterministic graph is an enriched graph representation that can improve classification rate combining both local binary gray-scale difference information and local structure information of texture images. This result demonstrates that the proposed approach achieves a higher degree of robustness to texture images in uncontrolled environments.

The third hypothesis of this thesis is:

- The efficacy of discrimination the original complex network model can be improved from uncontrolled environment databases if integrating between the new graph connectivity measurement and the enriched graph representation is proposed. The completed local textural information from the graph representation is more robust than the local structure information from the new graph connectivity measurement for uncontrolled environment database.

This hypothesis has been validated into two aspects: spatial vector-based graph representation and spatial encoding of texture pattern, which is a new graph connectivity measurement. Firstly, as it is reported in Chapter 3 and Chapter 4, the proposed graph connectivity measurement approach by local spatial pattern mapping (LSPM), significantly improve classification rate the degree of node, as proposed in the traditional complex network model [16]. Secondly, as reported in Chapter 4, the enhanced deterministic graph by decomposing the image local differences into the spatial vector property, the magnitude and the direction, improving the discrimination capability of the proposed approach in Chapter 4. From these two aspects, in Chapter 5, this thesis proposed hybrid-based complex network model for texture classification which integrates the enriched deterministic graph and spatial encoding schemes as the graph connectivity measurement. The experiments have been evaluated by comparison the classification rates of the degree of node (Deg) and LSPM, as graph connectivity measurement. This result demonstrates that the enriched deterministic of graph approach achieves a higher degree of discriminative capability than enriched graph connectivity measurement. On the one hand, the comparison results between the Deg and the LSPM achieves similarity classification performance. Therefore, the experimental result validates this hypothesis that the hybrid-based complex network model is able to enhance the original complex network model through employing the enhancing deterministic the graphs.

6.4 Limitations of complex network model in texture analysis

The complex network is investigated how texture image can be adequately represented, characterized and analyzed in terms of a complex network with impressive results. The advantage of the compromise between local and global properties and the interplay between structural and dynamical aspects can provide valuable information about the structure being analyzed. Accordingly, the Complex Network Theory, the success in texture discrimination demonstrates the potential of the application of this approach in computer vision problems and digital image processing. However, it may not necessarily be the best solution to apply in advanced applications such as robot manipulation, real-time application problems.

It is important to notice that the graph-network model is derived from the Euclidean distance between pixels and the difference of pixel intensity and neighborhood. The local discriminative information by complex network model is obtained in the deterministic the graph, the weight of edge. Euclidean distance calculates the spatial relevant. We can see that the proper optimization and/or normalization of these parameters do not apply to the process. A set of threshold value applies for imitation the dynamic transformation in the network. However, the optimized this parameter is essential for analyzing and extracting information. This approach could be explored in more detail using topology of graph methods and more mathematical model.

The unique spatial pattern mapping has proposed for encoding the spatial arrangement of the local binary pattern. In Chapter 3, we generated radial distance pattern mapping as three patterns based on Euclidean distance, then mapping them as a circular. However, the topology pattern structure for mapping should be more concerned and investigated, along with the number of the neighborhood that relevant in each pixel.

6.5 Future work

Future research can be considered to overcome the limitations of the proposed approaches, to explore other research paths and to continue to advance the field of texture analysis using the complex network.

Biological image processing-related texture datasets could be used to explore other research paths. They could now be applied to various texture problems and, in particular, in biomedical imaging for the segmentation and recognition. For instance, recognition of lesionsS and cancers or the analysis of temporal textures exhibited in sequences of ultrasound or X-rays.

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