CHAPTER 1

INTRODUCTION

1.1 MOTIVATION

Images and graphics are among the most important media formats for human communication and they provide a rich amount of information for people to understand the world. With the rapid development of digital imaging techniques and internet, more and more images are available to public. Consequently, there is an increasingly high demand for effective and efficient image indexing and classification methods, and image classification has become one of the most popular topics in the field of pattern recognition and image mining. Image texture, defined as a "*function of the spatial variation in pixel intensities (grey values)*", is useful in a variety of applications and has been a subject of intense study for many researchers. It is applied to many practical vision systems, such as biomedical imaging, ground classification, segmentation of satellite imagery, and pattern recognition.

Pattern recognition in images is an essential aspect of computer visioning in artificial intelligence. The aim is to recognize patterns depending on available knowledge, information or features. Generally, pattern recognition applications consist of three main stages: preprocessing, feature extraction and recognition/classification. In the preprocessing stage, the input image is prepared by removing the noise, correcting the skew, converting the image into a scoped format, and segmenting it into a sub-image pattern or normalizing it into an image block. During the feature extraction stage, an input image is transformed into feature representations containing discrete information, which is used during the recognition/classification stage for classifying known or unknown patterns [38].

1.2 IMAGE ANALYSIS AND CLASSIFICATION

Image analysis usually refers to processing of images by computer with the goal of finding what objects are presented in the image [78]. One immediate application of texture is the recognition of image regions using texture properties. One can identify different textures and their identities with different texture features or primitives. Texture is the most important visual cue in identifying these types of homogeneous regions in an image. An texture classification system is a computer system for browsing, searching, recognizing, comparing and classifying images from a large volume of digital images. The goal of texture classification then is to produce a classification map of the input image where each uniform textured region is identified by the texture class to which it belongs. Texture classification is one of the most important techniques used in image processing and pattern recognition, mainly motivated by the fact that it can motivate information about the arrangement and spatial properties of image fundamental elements. A good understanding of a more satisfactory interpretation of imagery should include the description of both spectral and textural aspects of the image, such as in the interpretation of remotely sensed data, biomedical or microscopic images. In texture classification the first and most important task is to extract some features which efficiently embody information about the characteristics of the original image. These features can then be used for the classification of different images.

A model of texture classification system is presented in the Figure 1.1, it can be seen that all the data, to be processed by the classification systems, first passes through a preprocessing stage. The preprocessing should serve two purposes. First, it should normalize the data to eliminate undesirable effects such as changes in illumination, resolution, digitization, etc. The next step is texture feature extraction. Texture feature extraction is the procedure of generating descriptions of a textured surface in terms of measurable parameters. For example, used features may be the local luminance, the texture (described with measures such as the entropy, the co-occurrence matrices, etc.), the contours (described with their length, their orientation, their relative position to other contours, etc.) [76, 86]. Most of the time, a third stage is necessary to reduce these features, because they are too numerous. The extracted features represent the relevant properties of the surface, and may be used with a classifier. In this stage, the numerical descriptors are fed to classification algorithms, which are application independent, such as Support Vector Machine [12, 19, 34, 35, 64], neural networks [40, 47, 77, 83, 84, 95, 101], k-nearest neighbors [43, 45], etc. The classification algorithms will decide, depending on their entries, which is the class of the image. It is commonly agreed that textural features play a fundamental role in classifying texture surface and texture segmentation. Feature extraction is concerned with the quantification of texture characteristics in terms of a collection of descriptors or quantitative feature measurements, often referred as a feature vector. The choice of appropriate descriptive parameters will radically influence the reliability and effectiveness of subsequent feature qualification through classification.

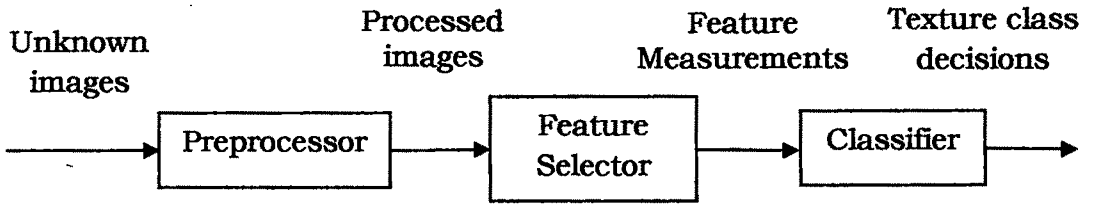

Figure 1.1: Block diagram of texture classification system.

1.3 LITERATURE SURVEY

Analysis of texture requires the identification of proper attributes or features that differentiate the textures for classification, segmentation and recognition. Various feature extraction and classification techniques have been suggested in the past for the purpose of image analysis. Initially, texture analysis was based on the first order or second order statistics of textures [15, 20, 25, 30, 110]. Then, Gaussian Marko random field (GMRF) and Gibbs random field models were proposed to characterize textures [14, 16, 18, 21, 41, 65]. Later, local linear transformations are used to compute texture features [44, 97]. The traditional statistical approaches to image texture analysis such as *'Gray level Co-occurrence Matrices'* (GLCM), second order statistics, *'Gaussian Markov Random Fields'* (GMRF), and *'Run Length Matrix'* (RLM) [27] are restricted to the analysis of spatial interactions over relatively small neighborhoods on a single scale. As a consequence, their performance is best for the analysis of micro-textures only [98]. Moreover, they are single resolution techniques, resulting in poor performance for texture analysis. He and Wang [31] proposed a texture spectrum based method, which stated that a texture image is considered as a set of small texture units, which characterize the local texture information for a pixel and its neighborhoods and then used a clustering algorithm for unsupervised classification. However, most of existing methods are more or less sensitive to the changes in rotation, scale, or illumination of images.

Recently, a new feature set derived from the fractal geometry called the *'Random Threshold Vector'* (RTV) is proposed for texture analysis [85]. The RTV is computed for different run length entropy dimensions. The run length entropy dimensions are calculated based on different thresholds. Texture characterization method based on *'Fuzzy Texture Unit'* (FTU) for texture synthesis is proposed [100]. The proposed fuzzy texture characterization approach [46], takes into account the vagueness introduced by noise and the different caption and digitization processes, for defining the texture unit, by which texture synthesis is obtained. The *'Local Binary Pattern'* (LBP) operator, first introduced by Ojala et al. [69], is a robust but theoretically and computationally simple approach. It brings together the separate statistical and structural approaches to texture analysis of both stochastic micro textures and deterministic macro textures simultaneously. A combined statistical and structural approach [96] is used for texture representation. A set of texture primitives are suggested. These primitives are basically tested for the presence of texture by conducting a suitable statistical test called Nair's test. Later, the original LBP operator [69] has been extended in several ways, such as neighborhoods with different sizes [94], multi-resolution [62, 73], uniform patterns [73], centre symmetric LBP [63, 37] etc. The extended LBP operator can be used for texture analysis and classification [6, 42, 59, 60, 61, 68, 70, 71, 72, 73, 75, 79, 81], face detection and recognition [7, 13, 26, 33, 39, 90, 92], image retrieval [91, 28, 61, 82], etc. The LBP algorithms yield good classification results on large and complex databases [32, 52, 80, 99].

More recently, several methods are proposed for classification of textures Antonio etal [9], Loris Nanni etal [55], Bilal Bataineh etal [10], Xianglin Meng etal [113], Zhiqiang Zheng etal and Marko Heikkil" etal proposed CS-LBP[37, 63], LRTUM [88] by Sujatha etal proposed, Completed LBP [116], Bongjin Jun etal [11], Texton co-occurrence matrix [28], Multi-texton histogram [29], Fuzzy texture spectrum [8, 66, 111, 112] have received a lot of attention. But so far no extensive work is done on fuzzy based image texture classification based on statistical approach. Due to this reason, the present thesis mainly focused on fuzzy local pattern approach for image texture classification.

1.4 OBJECTIVES OF THE PRESENT STUDY

The major objective of the present thesis is to contribute to increase the quality of the texture classification by reducing the dimensionality, and reducing the computational cost derived from unnecessary features. The specific objectives of the present study are:

1. To deal accurately with the regions of natural images derived from TU even in the presence of noise and the different processes of caption and digitization.
2. To derive a new GLCM based on centre symmetric principles on TU for efficient classification that reduces the size of the dimension of the matrix from 6561 to 67 in the case of original texture spectrum and 2020 to 67 in the case of *'Fuzzy Texture Spectrum'* (FTS) approach.
3. The overcome the disadvantage of the *'Left and Right Texture Unit Matrix'* (LRTM) by considering the texture unit numbers from all the 4 different LRTM's instead of the minimum one as in the case of LRTM.
4. To derive connected approaches of TU that reduces the dimensionality for an efficient classification and to overcome the non connected approaches of TU like *'Cross Diagonal Texture Matrix'* (CDTM) or Modified CDTM.

5. To derive theoretically simple yet very effective statistical texture descriptor in terms of the characteristics of the local structure, for an efficient image classification.
6. To overcome the disadvantages of ULBP and NULBP and to derive SULBP for an efficient image classification.
7. To derive a modified LBP that overcomes the effect of noise and illumination.
8. To derive a run length matrix on LBP using fuzzy principles for efficient image classification.
9. To overcome the problems of missing local information, noise and contrast in LBP.
10. To derive new matrices with low dimensionality based on texture unit and LDP concept using fuzzy logic that suits the GLCM – which is the benchmark approach for texture classification.

1.5 SCOPE OF THE PRESENT STUDY/ BRIEF OUTLINE OF THE THESIS

To achieve above mentioned objectives for image texture classification using statistical features, the thesis is divided into six chapters.

The first chapter deals with introduction, literature survey, problem identification, objectives and scope of the present study and with names of VisTex, OuTex and Granite textures that are taken on experimental basis in this thesis.

Chapter two introduces the concept of GLCM and texture unit (TU).

Chapter three of the present thesis combines the *'Centre symmetric Fuzzy Texture Unit'* (CSFTU) and *'Co-occurrence Matrix'* (CM) approach to derive a novel texture descriptor called CSFTU-CM, which drastically reduced the texture unit number from 0:6560 to 0:66 and provides an efficient, precise, and computationally inexpensive texture classification [102]. Further the proposed CSFTU-CM, of chapter three, reduces the size of the matrix from 2020 to 67 as in the case of FTU approach. The CSFTU-CM approach considers only one set of four connected texture elements on a 3×3 grid for evaluating the FTU instead of non-connected or corner texture elements as in the case of *'Cross Diagonal Texture Unit Matrix'* (CDTM).

Chapter four extended the concepts of chapter three and combines the left and right fuzzy patterns with a new texture feature descriptor called *'Average Fuzzy Left and Right Texture Unit'* (AFLRTU) for texture classification [103]. The proposed scheme also overcomes the disadvantage of the *'Left and Right Texture Unit Matrix'* (LRTM) by considering the texture unit numbers from all the 4 different LRTM's instead of the minimum one as in the case of LRTM. The proposed CSFTU-CM reduces the size of the TU matrix from 6561 to 67 in the case of original texture spectrum and 2020 to 67 in the case of *'Fuzzy Texture Spectrum'* (FTS) approach. Thus, it reduces the overall complexity. The co-occurrence features extracted from the AFLRTU matrix provide complete texture information about an image, which is useful for texture classification.

To overcome the noise effect on LBP the present study derived '*Local Directional Pattern*' (LDP) using Kirsch mask in chapter five. The present study found that ULBP have some shortcomings: they discard some important image information, suffer much from non-monotonic illumination variation and do not describe the stochastic characteristics of texture efficiently and sensitive to noise. To overcome this, the present thesis defined '*Semi Uniform LBP*' (SULBP) on LDP. The novelty of the proposed method is, the Haralick features are applied on the derived SULDP-CM, which has shown excellent classification results by reducing the overall dimension of the derived matrix dimension, thus reducing the overall complexity.

Chapter six proposes a novel local texture descriptor based on the '*Run Length Matrix*' (RLM). The proposed RLM is constructed on the Local Binary pattern using fuzzy principles. The proposed '*RLM on Fuzzy LBP*' (RLM-FLBP) [104] overcomes the disadvantages of the previous run length methods of texture classification that exist in the literature.

The seventh chapter gives conclusions and future scope of the present thesis. Further at the end of each chapter, a summary is provided. The experimental results of the present thesis clearly indicate the simplicity and novelty of the proposed methods.

1.6 IMAGE DATABASES

The performance of the proposed methods are tested with three texture datasets, which are derived from three popular publicly available texture databases namely, the Outex, the VisTex, and the Granite databases. The OuTex dataset [74] is composed of 45 texture classes (one image for each class) from the OuTex library as shown in Figure 1.2. The size of the original images is 746×538 pixels. As the texture surface rotates, only the central part of the image captures the same portion of the surface. For this reason, the central part of the rotated images is retained which is calculated by $(\min(W,H)/\sqrt{2})$ where W and H are the width and height of the original images. This gives an image size of 380×380 pixels. Each image is subdivided into 16 non-overlapping sub-images, giving a database of 720 texture samples (16 for each class). The granite database [9] is composed of 12 granite texture classes. The overall dataset is composed of 48 images, 4 for each class as shown in Figure 1.3. VisTex database [106] is to provide texture images that are representative of real world conditions and it contains 1188 images, few of them are represented in Figure 1.4 respectively

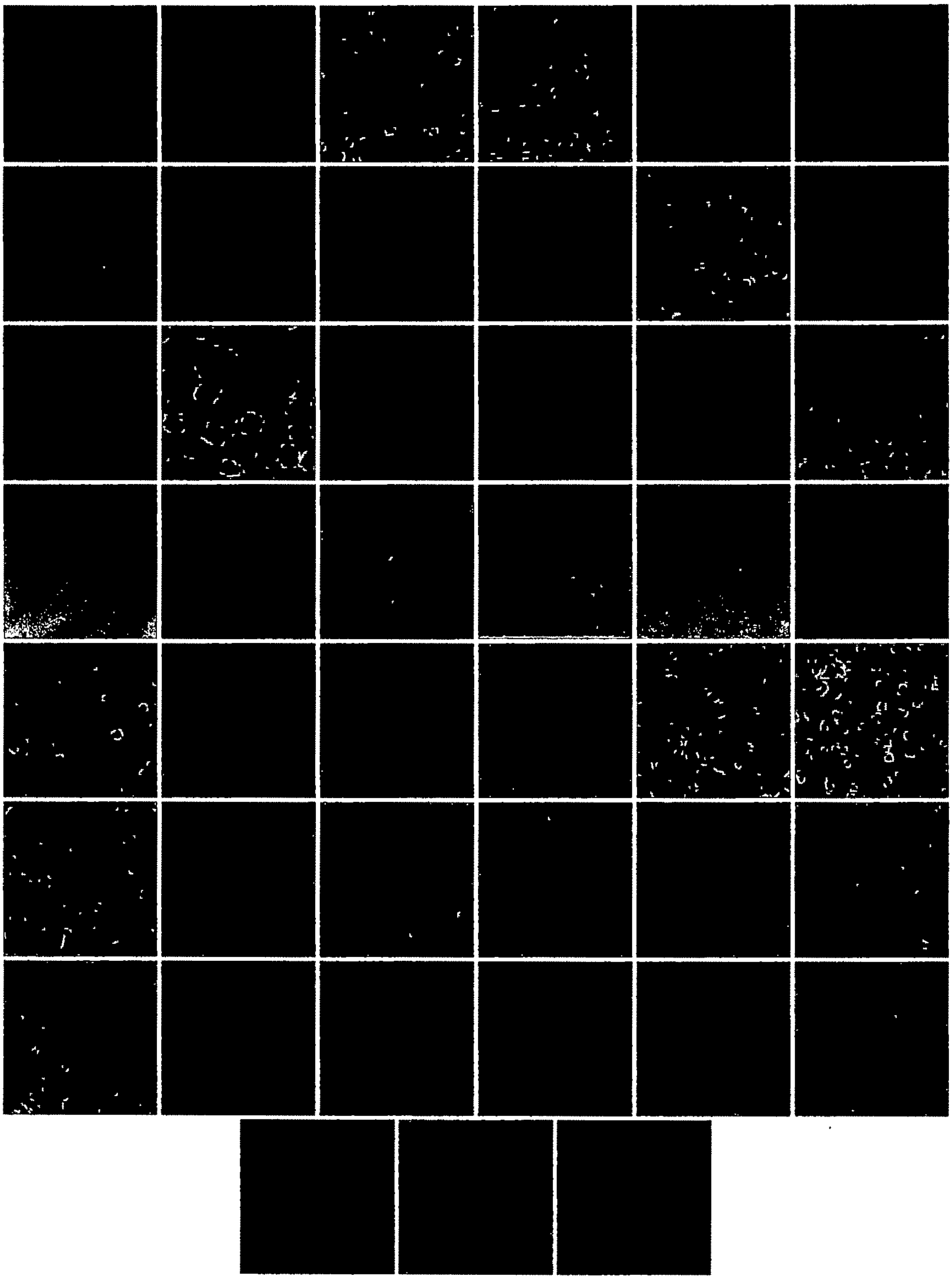

Figure 1.2: Dataset-1: 45 texture classes (one image for each class) from OuTex. Canvas{005, 021}; Carpet{005}; Granite{001, 003, 004, 005, 006, 007, 008, 009, 010}; Paper{006}; Plastic{001, 002, 003, 004, 005, 009, 016, 017, 018, 019, 020, 021, 022, 023, 024, 025, 026, 027, 028, 029, 030, 031, 032, 033, 034, 035, 036, 038, 040, 041}; Wood{006, 008}.

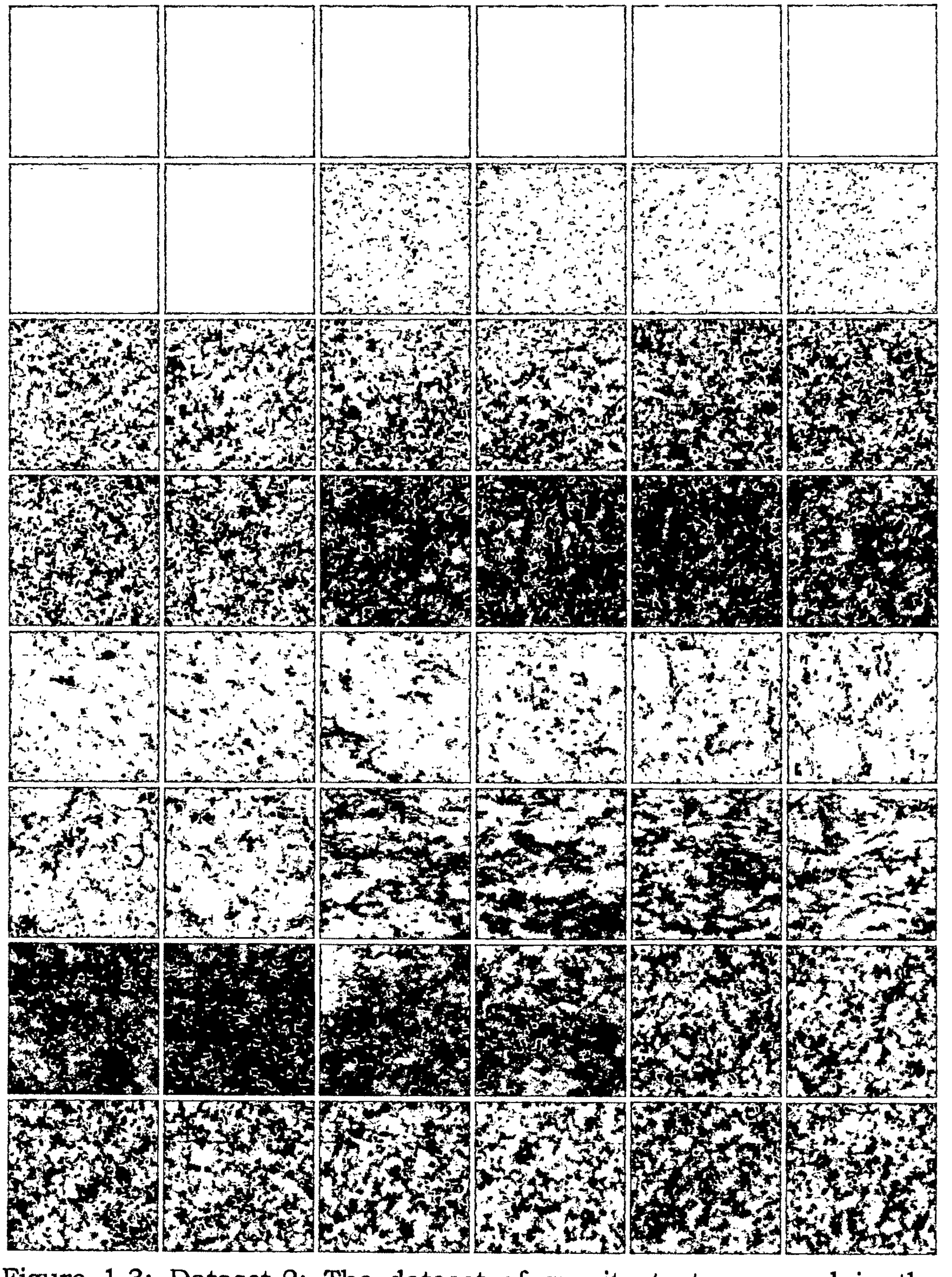

Figure 1.3: Dataset-2: The dataset of granite textures used in the experiments (unrotated images). From the top: Acquamarina, Azul Capixaba, Bianco Cristal, Bianco Sardo, Rosa Beta, Azul Platino, Giallo Ornamentale, Giallo Napoletano, Giallo Santa Cecilia, Giallo Veneziano, Rosa Porri˜no A, Rosa Porri˜no B.

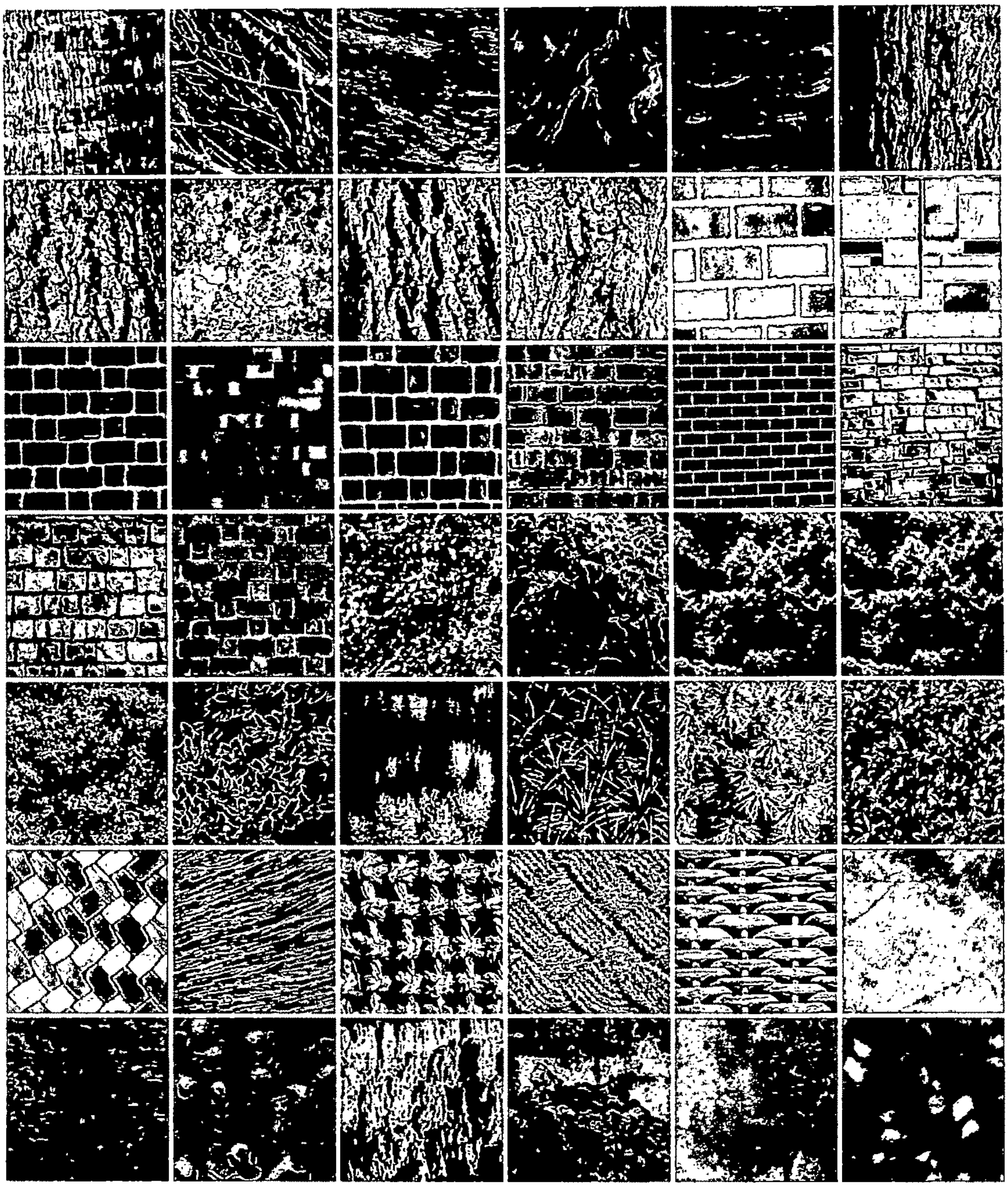

Figure 1.4: Vistex Database: Bark.0000, Bark.0001, Bark.0002, Bark.0003, Bark.0004, Bark.0005, Bark.0006, Bark.0007, Bark.0009, Bark.0010; Brick.0000, Brick.0001, Brick.0002, Brick.0003, Brick.0004, Brick.0005, Brick.0006, Brick.0007, Brick.0008, Brick.0009, Brick.00010; Leaves.0000, Leaves.0001, Leaves.0002, Leaves.0003, Leaves.0004, Leaves.0005, Leaves.0006, Leaves.0007, Leaves.0008, Leaves.0009, Leaves.0010; Fabric.0000, Fabric.0003, Fabric.0005, Fabric.0006, Fabric.0007; Stone.0000, Stone.0001, Stone.0002, Stone.0003, Stone.0004, Stone.0005.