

VISUALIZING 3-D TEXTURE: A THREE DIMENSIONAL STRUCTURAL
APPROACH TO MODEL FOREST TEXTURE.

by

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ABSTRACT

The evaluation of texture in digital remote sensing, is traditionally accomplished by applying statistical, rather than structural models. This approach is partially due to the difficulty in determining structural placement rules for natural scenes, and to early psychophysical texture theories that demonstrated humans were sensitive to second-order statistics. A literature review indicates that these statistical theories are now considered inaccurate discriminators of visual texture, yet they are still incorporated within current remote sensing texture practices. As a result, four recognizable areas of discrepancy exist between human texture perception, and digital remote sensing texture methodology. These discrepancies include:

1. Defining appropriate primitives.
2. Quantifying the spatial arrangement of primitives.
3. Determining appropriate scale / spatial resolution.
4. The inclusion of depth information.

To overcome these discrepancies, a structural texture methodology referred to as the triangulated primitive neighborhood method (TPN) has been developed based on current psychophysical texture theory. Though similar to the grey level cooccurrence matrix method (GLCM), this technique reduces many of the user specified requirements and inadequacies of the GLCM by incorporating object specific height and area data, location specific primitives, and a variable sized and shaped moving window to produce digital texture features approximating human perception. In this study, a simple unsupervised classification of Neighborhood Height and Neighborhood Area data sets provide a visually correlative perception of the within- and between-stand texture of two different aged forest stands.



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Appendix 2), and assigned back to the associated TP region. This results in a new data set, where each pixel located within a TP is normalized to a single value (specific to that TP), representing one structural characteristic of the *portions* of the OP's within its boundary.

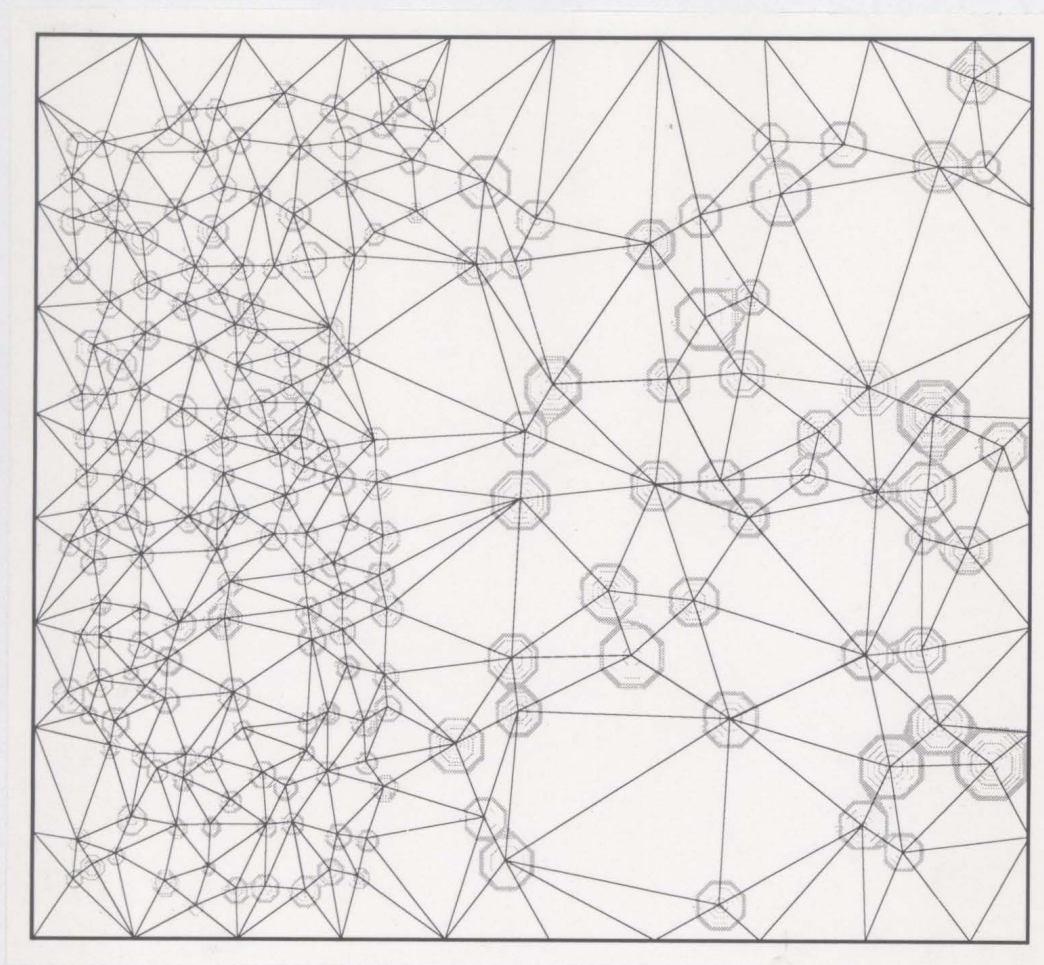


Figure 5.8 This graphically illustrates the portions of three trees (OP's) located within each Delaunay triangulated TP, that the program PIP (Point_in_Polygon), could assess for crown structure information. Visually, each (non-perimeter) TP spatially represents the crown density of 3 trees within its perimeter.

Height information relating to the OP's located within a single TP, is extracted by the routine PIP, in the following manner:

1. Determine by a point in polygon routine, the location (x, y) and number (n) of all pixels that constitute the 3 OP's residing within the single triangular TP (f) (see figure 5.9). **Note:** All OP information comes from a H-resolution DCM data set (figure 5.5) where all tree information is equated to DN values over 0.0 m in height, and where each pixel represents a 0.1 m x 0.1 m spatial region.

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To the graphics' gurus Ken and Ole, the 17 grad's who entered geography at the same time as myself 2 short years ago, and to my long distance fishing partner and remote sensing - e-mail buddy Greg McDermid, thank you. You have all made a difference.

DEDICATION

To my Father, who encouraged my questions about the world.

To my Mother, who encouraged me to dream,

and to my Wife,

who, for the last two years has indulged a dyslexic absent minded scientist,
intrigued by teh wonders of texture.

CHAPTER ONE

INTRODUCTION

Casual experience with the phenomenon *texture* belies the complex and diverse nature of the domain designed to understand, define, and emulate what we intrinsically perceive it to be. Within a paradigm that includes music, artificial intelligence, vision, pattern recognition, haptics, remote sensing, textiles, and psychophysics, countless texture definitions exist; there is simply no singly accepted definition (Haralick 1979; Lederman et al., 1986).

Originally the term 'texture' is adopted from textiles, where it refers to the weave of various threads - loose or tight, even or mixed (Kerman 1980). A cloth such as tweed is composed of different, clearly visible threads. In fine silk or percale, the weave or structure of the cloth surface is so tight and smooth, that individual constituent threads are difficult to detect. Take a moment, and try this 'thought experiment'. Go back to the beginning of this paragraph, and as you reread the description, visualize in your 'minds eye' the weave, or the structural layout of the various threads: tweed, silk and percale. In the mental images you form, try to 'see' the size, shape, and spatial arrangement of the various threads described. Go ahead.

This process of 'seeing', unrestricted by human eyes, is termed *visualization*; and in the proceeding pages is considered synonymous with 'perception'. Visualization is the process of portraying information synoptically for the purpose of recognizing, communicating, and interpreting pattern and structure. Its domain encompasses the computational, cognitive, and mechanical aspects of generating, organizing, manipulating and comprehending such representations (Buttenfield and Mackaness 1991). Throughout the formulation of this research, this process has proven invaluable.

Intrinsically, many of us have an understanding of what texture is, and if asked to define our perception of a textured surface could provide an answer; but to singularly quantify a perception that differs from person to person is an onerous undertaking. To make matters worse, perceptions of texture are not restricted to a single sensory input. Commonly, they may be obtained from combinations of vision, touch, and audio cues. Smell and taste

appear less well researched. Since our visual and haptic (touch) systems provide significant information about the physical world (Heller 1982; Garbine and Bernstein 1984; Jones and O'Neil 1985), only texture information perceived through these modalities, will be explored in this thesis. The term *human texture* will be used to represent texture information obtained through these two senses.

Texture is an important characteristic of form perception (Uttal 1983, 1988) used by humans to perceive and quantify both real-world scenes, and remotely sensed images of real-world scenes (Jensen 1986). It intrinsically provides structural information to the interpreter, in the form of the spatial arrangement of objects, region discrimination, surface orientation, and shape in 2 and 3-D environments (Gibson 1950, 1962; Lederman et al., 1986; Klatzky et al., 1987). In remote sensing (RS), texture analysis typically involves quantifying the spatial variation of tones or intensities in a 2-D image (Haralick 1973; Marceau et al., 1990). In human texture analysis, texture involves quantifying the physical size (Bergen and Adelson 1988), shape (Klatzky et al., 1987), and spatial arrangement (Julesz 1975, 1981) of the components that constitute a 3-dimensional scene, so that regions with similar structural characteristics may be delineated (Uttal 1983, 1988).

It is important to recognize, that although the RS technology and theory are sophisticated, the current approach to classification still relies on a variety of supervised enhancement techniques to facilitate visual interpretation (Marceau 1992); yet many of our modern theories do not accurately emulate what the human visual system does. After researching many different sources of texture literature, it became apparent that much of the present RS texture methodology is founded on dated second-order statistical vision texture theories, which - originally developed in psychophysics (Julesz, 1962, 1975) - are no longer considered a valid quantifier of visual texture perception. In psychophysics (see Chapter Two), this dated theory has been refined, allowing it to evolve into newer theories. Unfortunately, such a refining process has been slow to occur within RS, resulting in many of the same limited texture techniques developed 20 years ago, still being used today e.g., the poor classification results of texture features based on Fourier power spectra (Weszka et al., 1976; Julesz, 1983; Gu et al., 1991), and the complications of a static sized window in GLCM's (Marceau et al., 1990; Franklin and McDermid, 1993). My attempt to identify, understand, and overcome several of these limitations is the basis behind this thesis.

Based on this, the proceeding four sections are intended to identify several key terms and concepts used throughout the body of this work, and to introduce four important and interconnected discrepancies that exist between human texture perception and current RS texture analysis. These involve:

1. Defining appropriate primitives.
2. Quantifying the spatial arrangement of primitives.
3. Determining appropriate scale / spatial resolution.
4. The inclusion of depth information.

Following this, the objectives and basic organization of the thesis will be outlined.

1.1 Primitives

Primitives, scale, and spatial arrangement are closely intertwined in a texture description. It is difficult to describe one, without inferring the others. At the appropriate level of resolution, texture is an innate property of all surfaces. It describes the structure of a surface by intrinsically informing us about the physical and spatial attributes of the elements that constitute it, e.g., the size, shape, and spacing of the weave in a fabric, crops in a field, bark on a tree.

In these examples, the weave, the crops, and the bark are the resolvable constituent elements of the specific surfaces being defined (i.e., the fabric, a field, and a tree). These primary, resolvable elements (at a constant scale) are central to understanding texture, and are referred to as *primitives*. Marr (1982) regards them as the most elementary building blocks, or units of shape information available in a surface (representation). Implicit to the building block analogy is the idea of aggregation and appropriate scale: viz., smaller related primitives can be grouped together to build the objects of analysis. For example, if we assume the objects or primitives of interest are trees, then leaves or needles (symbolizing a low level primitive) could be organized and grouped to represent a specific type of tree (which symbolizes a higher level primitive). Once the appropriate objects (trees) have been defined, analysis could then proceed on them, resulting in substantially different results than if analysis was confined to inter-leaf primitives.

Marr (1982) indicates “...it is of critical importance that the tokens (primitives) one obtains, corresponds to real physical changes on the viewed surface; the blobs, lines, edges, groups and so forth that...are used...must not be artifacts of the imaging process, or else inferences made from their structure backwards to the structure of the surface will be meaningless” (p.91).

In RS texture, the primitives of analysis are individual pixels, which represent one from many possible spatial sampling units of the same scene, modifiable at choice according to the sensor design. Additionally, they do not correspond to objects on the ground - if they did, they would vary considerably in size and shape (Marceau 1992). In human texture perception, the primitives of analysis are discrete entities, or objects, that extend across pixel boundaries (Li and Strahler 1985; Lederman et al., 1986; Klatzky et al., 1987).

1.2 Spatial Arrangement

The idea of interrelationships, or spatial organization among primitives is fundamental to an understanding of texture. Texture is an aggregate quality of a surface, it does not exist for a single point, or primitive (Tamura et al., 1978). In many recognition problems involving complex patterns, it may be appropriate to view a surface as being composed of the interrelationships among the primitives (Jain 1987). For example, in a (1:15 000 scale airphoto) forest scene, individual trees - defined by their spatial and spectral crown dimensions - could represent the primitives of analysis, which as a group form the complex pattern (surface structure) of a stand or forest with its associated texture. These relationships can be defined ranging from regular, to random (Van Gool et al., 1983); though it should be noted that ‘real scenes’ are not chaotic or random but manifest spatial and temporal order (Strahler et al., 1986).

In computer vision (Chapter 3), two broad classes of texture discriminating techniques are used to evaluate the spatial arrangement and characteristics of primitives. They are referred to as the Statistical and Structural models. Statistical models usually describe texture by statistical rules governing the distribution and relations of grey tones, while, Structural models regard primitives as forming a repetitive pattern, and describe such patterns in terms of rules for generating them (Ballard and Brown 1982). In RS, the grey level cooccurrence

matrix method (GLCM) - typically employing second order statistics and a fixed sized window - appears the standard procedure used to evaluate the spatial characteristics of image texture (Haralick 1979; Franklin and Peddle 1990; Gong et al., 1992); yet, recent psychology findings (Chapter Two), indicate that second-order statistics, and a static sized window are inadequate to represent human visual texture (Julesz 1981; Julesz and Bergen 1983).

1.3 Scale / Spatial Resolution

Scale represents a concept by which proportions within and between objects can be described; as a result, it is an intrinsic spatial property of any phenomenon (Marceau 1992). In cartography, a formal definition of scale involves an expression indicating that one unit of distance on a map or photograph represents a specific number of units of actual ground distance (Lillesand and Kiefer 1987). In RS, a fundamental characteristic of an image is spatial resolution, or the size of the area on the ground from which the measurements that compose the image are derived. In this sense, spatial resolution is analogous to the scale of the observations (Townshend 1980, in Woodcock and Strahler 1987) and will be considered in this manner throughout the remainder of this thesis.

In nature, scales of phenomena are not arbitrary, but tend to concentrate around discrete states as a function of the physical laws that dominate at each level (Klemes 1983 in Marceau 1992). Marr (1982) states that the features of a shape that are much smaller than the primitive used to describe it are not just inaccessible, they are completely omitted from the description. Thus, the size of the primitives used in a description determines to a large degree the kind of information made explicit by a representation, the information made available but not directly obtainable, and the information that is discarded.

In RS, most primitives (pixels) are of a spatial resolution inappropriate for the extraction of *object specific* information (Marr 1982; Cohen and Spies 1992; Woodcock and Strahler 1987). It has been suggested that in order to detect a feature, the spatial resolution of the sensor should be less than half the size of the feature measured in its smallest dimension (Jensen 1986). In (low) L-resolution imagery where resolution cells are larger than the real world objects e.g., Landsat Thematic mapper (TM), or Multispectral scanner system (MSS) satellite data, a single pixel potentially represents an unknown number of non-

resolvable objects, in unknown spatial arrangements. In medium to (high) H-resolution imagery e.g., Compact Airborne Spectrographic Imager (CASI), and Multispectral Electro-optical Imaging Sensor (MEIS) data, resolution cells are smaller than real world objects (Strahler et al., 1986); as a consequence, an individual pixel potentially represents a portion of a single object.

The MSS and TM sensor systems developed in the 1970's and early 1980's, provided imagery with spatial resolutions of from 79 x 79 m to 30 x 30 m. It has only been since 1986 with the advent of System Pour l'Observation de la Terre (SPOT) that 10 x 10 m panchromatic and 20 x 20 m multispectral satellite information has been available for public use (Jensen, 1986). While SPOT provides a dramatic improvement over previous sensor data, the spatial and spectral resolution are still too coarse to be used as the primary data source for detailed forest inventories. Most Canadian forests are composed of trees with crown dimensions much smaller than 20 x 20 m, and SPOT panchromatic images alone, are not suitable for species level discrimination.

The trend in previous and current RS texture research involving L-resolution imagery of natural scenes, is for a single pixel (generalized by a sensor to represent an average measure of electromagnetic radiation (EMR), reflected from non-resolved real world objects) to be used - in combination with neighboring pixel's - to distinguish the *texture* of individual forest primitives the sensor is unable to detect. This is not satisfactory. As RS technology matures, more sophisticated imaging tools are being developed that provide for the collection of H-resolution data; but analyzing this data is not without its own problems. As the spatial resolution of the sensor increases, the spectral variation of the data set tends to dramatically increase, resulting in a reduction of statistical separability with current classification techniques, and a reduction in classification accuracy (Woodcock and Strahler 1987). Obviously then, increasing the spatial resolution alone is insufficient. The solution to greater RS accuracy and validity of information, must lie in refining old techniques, and developing new methodologies, to handle the increasingly new types of data.

1.4 Depth

Computer vision (CV) is a diverse paradigm including artificial intelligence, pattern recognition and RS (see Chapter 3). Essentially, its goal is to develop methods to 'teach'

computers to 'see' or to visualize their environment (Peuquet 1988). Yet within CV, texture is considered nearly exclusively a 2-D research topic. This restriction is founded on the premise that the three-dimensional 3-D world is mapped onto our 2-D retinae (Julesz 1975; Marr 1982; De Valois and De Valois 1988). While this perception may be convenient for computer programming, humans live and function in a 4-D world composed of 3-D entities, where haptic and visual texture cues employing depth information are interpreted and considered important.

Visual depth information is readily available from a monocular image via: size perspective (diminution of size with distance), motion parallax, areal perspective (haziness, etc. associated with distance), occlusion effects, outline continuity (complete objects look closer), and surface shading variations (Jarvis 1983; Horn 1989). Binocular or stereo vision has evolved in humans, to provide both absolute and relative depth perception (De Valois and De Valois 1988); and the action of simply reaching out and feeling the relative proximity of objects around us, creates a haptic impression of depth. Yet the inclusion of this important spatial dimension, at least within RS texture methodology, is almost non-existent.

1.5 Thesis Objectives

While many different texture segmentation strategies exist in digital remote sensing (Van Gool et al., 1983), GLCM's remain the standard procedure against which many texture analysis methods are currently evaluated (Du Buff et al., 1990; Gong et al., 1992); despite the fact, that the statistical methodology, and static-sized window they use have been shown inadequate to represent human visual texture (Julesz 1983). Not only this, but the texture primitives used in remote sensing are individual pixels which do not correspond to objects on the ground; if they did, they would vary considerably in size and shape (Marceau 1992). They also employ no height or depth information, and they are usually of a spatial resolution inappropriate for the extraction of object specific information (Woodcock and Strahler 1987; Cohen et al., 1990; Marceau 1992).

If digital RS texture analysis is to approach human texture analysis, image primitives (pixels) need to be of a sufficient spatial resolution to represent parts of real world objects, then these object parts need to be grouped into shapes representing real world objects.

Once this is accomplished, analysis of the 3-D structural qualities of these newly formed object primitives (OP's) can be performed; ideally within a scale varying moveable window similar to the human visual system (section 2.2.2).

Based on the four described differences that exist between human texture perception and remote sensing texture analysis (page 3), the objectives of this investigation are:

1. Inform the RS community that current digital texture methodology is premised on findings that are now erroneous, and that change is required.
2. Develop and evaluate a structural texture methodology, that incorporates the key characteristics of human texture perception, to determine the within- and between-stand texture of 2 different age class forest stands.
3. Demonstrate the importance of defining object oriented primitives that represent the three dimensional structure and location of real world objects, at an appropriate scale for texture discrimination to occur.
4. Emphasize the importance of using height information for the (object) figure-ground segmentation of a (high) H-resolution forest image.

1.6 Organization of the Thesis

To accomplish these objectives a more thorough comprehension of texture is required. The following three chapters will review visual and haptic texture paradigms; examine computer vision texture methodology, in particular the use of GLCM's as texture discriminators in digital remote sensing; identify the key characteristics and differences between RS, haptic, and visual texture discrimination; and discuss how psychophysical texture research has influenced current RS texture methodology. These chapters will be followed by the methodology section, describing the processes involved in developing the triangulated primitive neighborhood method (TPN) - a CV system developed to model and segment a textured forest scene, premised on recent human texture theory. The Results and Discussion section will then proceed, followed by the Conclusion.

CHAPTER TWO

PSYCHOPHYSICAL TEXTURE

Psychophysics is a branch of psychology that studies the effect of physical stimuli derived from an external world upon the psychological events occurring inside the perceiver (Gordon 1989). This discipline is uniquely responsible for important discoveries about the workings of the nervous system without entering or tampering with the system, resulting in one of the most notable contributions to experimental psychology.

Psychophysics is not a theory of perception; rather it is a set of techniques which experimental psychologists have developed over many years to measure sensory and perceptual thresholds: We know there are sounds we cannot hear, objects we cannot see, and odors we cannot smell, but when the 'strengths' of these stimuli are increased to certain levels, we may be able to perceive them. The specific level where the stimulus apparently changes from being non-perceptible, to perceived, is referred to as a *sensory threshold* (Gordon 1989). The following section reviews some of the important psychophysical vision and haptic research conducted to determine human texture thresholds, in the hopes of understanding more about human form perception.

2.1 Visual Theory - Julesz

In psychology, visual texture may be defined as aggregates of many small elements - either dots of certain colours, or simple patterns (Julesz and Bergen 1983) - as a result, texture discrimination is seldom limited to a single attribute, aspect or dimension of the visual stimulus, but rather, the interaction of multiple objects (Uttal 1988). In texture discrimination, the observer's task is to discriminate different regions from each other, on the basis of some organized attribute of the local geometry of the regions' constituents. The fundamental issue of what these attributes or properties are, has challenged the field of psychophysics for over two decades.

While many noted researchers have explored this issue (Beck 1966; Pollack 1973; Barlow 1978), most of the pioneering psychophysical texture-vision studies were conducted by Bela Julesz (1962). This section will review Julesz's two main texture discrimination

models: the Statistical and Texton models. In both models it is important to recognize that (1) Julesz's research is confined to preattentive texture analysis. That is, he is only interested in understanding the processes involving 'pure perception' (Julesz 1975) - tasks that can be performed 'spontaneously' (within 200 msec) - compared to scrutiny, which requires cognitive information processing. (2) Because the retinal image is considered two-dimensional (De Valois and De Valois 1988), the visual nervous system must be performing a 2-D analysis; consequently Julesz considers vision a 2-D process and conducts his analysis and modeling on 2-D dot patterns (or 2-D variations thereof). (3) Julesz considers texture to be defined by the nature of the arrangement, or organizational properties of the elements (dots) of a repetitive pattern, and (4) the primary research issue Julesz is trying to solve is: what are the attributes or properties of the textured visual stimuli that allow different textures to be instantly discriminated from each other?

2.1.1 The Statistical Model

Early texture research, while leading to important conjectures (e.g., surface density gradients as potential depth cues (Gibson 1950)) was mostly phenomenal in nature. Bela Julesz's idea of orders of statistical complexity (Julesz 1962, 1975, 1978; Julesz et al., 1973) as numeric descriptors of preattentive texture was the first quantitative texture model. The orders of statistical complexity proposed by Julesz and his colleagues are analogous to the moments (i.e., mean, variance, etc.) of descriptive statistics, and as previously indicated, are best understood if described in terms of dot patterns.

The *first* statistical order of texture (Julesz 1975) is closely associated with the mean number of dots in the stimulus, thus, the mean density. 'Stimulus' refers to the environment being analyzed. Because dot densities are related to the energy being emitted by a surface, regardless of whether the dots are black on a white background or vice versa, first-order texture is also linearly related to the luminance of a dotted stimulus pattern (Uttal 1988).

Julesz's *second* statistical order of (preattentive) texture, while less intuitive, describes an aspect of a dot pattern most closely related to the average spacing between dots, or the "clumpiness" or "clustering" of the dots. It is analogous to the variance (a measure of the spread of values around a central point) in ordinary descriptive statistics. Thus, two

textures might have identical first-order statistics (an equal numbers of dots in equal areas) but differ in their second-order statistics (which indicate the degree to which dots are bunched and separated) in a way that makes them appear very different (figure 2.1).

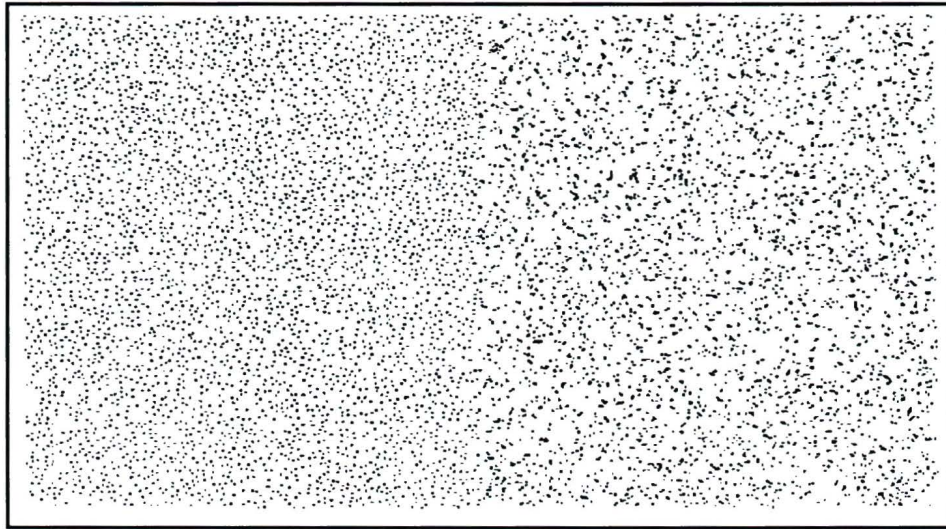


Figure 2.1 Two textured surfaces having the same first-order statistics (representing the number of dots) but differing in their second-order statistics (which indicates the clustering of the dots) (from Julesz et al., 1973).

Julesz's *third-order* (preattentive) texture statistics are even less intuitive, and less easily described. Conceptually, it is possible to consider them as a common property of the local geometry of the elements that make up the pattern, as opposed to the more global measures of density and clustering described by the first two orders. The third-order statistical test is described (Julesz 1975) by a sample triangle being 'thrown' (randomly) onto a number of places on two dot patterns. If on the average, the triangles corners fall on three dots the same number of times in the two patterns, the patterns are said to possess the same third-order statistics.

Based on these three statistical orders of textural complexity, two general properties have been identified:

1. If two patterns have identical statistics at one order, all lower orders must also be identical.

2. Higher order statistics, are independent of those of lower order. Just because statistics at one order are identical, does not indicate that the higher order statistics are identical.

It is as relatively simple to produce patterns identical in their first order, yet which differ in their second- and third-order statistics, as it is to create patterns that are identical in their second-order statistics (and consequent first-order statistics), yet which differ in their third-order statistics. Studies by Barlow (1978) and Burgess et al., (1981) substantiate that humans can discriminate first-order visual textural differences, though both cases indicate difficulty in differentiating very high densities. A study by Pollack (1971) serves as an example that second-order textural processing by the visual system is possible, though an apparent saturation of second-order discriminability also occurs when high dot densities were used.

2.1.2 Changing Ideas

Julesz (1975, 1978) had originally conjectured, that in general, if two textures had identical second- and (consequently, the same) first-order texture statistics, observers were not able to discriminate between them if they differed only in their third-order statistical properties. This may be explained by the relative efficiency of the visual system in measuring the surface density, and variance of inter-dot patterns (both considered by Julesz to be global texture variables), but that the processing requirements of the human brain to preattentively evaluate third-order differences (local properties) are too demanding. Julesz states (1975, p.35) "*... that when a certain image property cannot be perceived, it implies either that perception of the property was not crucial for our ancestors, or that the extraction of the property exceeds the processing power of the perceptual system.*" This may explain why it is difficult to intuitively understand the meaning of third-order differences. We have no experience in them...which leads one to ponder their relevance.

It is important to recognize that Julesz (1975) and his colleagues spent much of their time trying to create perceptual tasks at the extremes (the thresholds) of the visual system's processing capabilities (Tamura 1978). Some of the research involved in evaluating the third-order statistical properties of dot patterns (Caelli and Julesz 1978; Caelli et al., 1978),

indicated that dot patterns do exist with regions differing only in their third-order statistics, that are immediately segregated as effectively as if they had differed only in their first- or second-order statistics. This violation of Julesz's earlier 'conjecture' - that preattentive visual texture discrimination involves processes that cannot 'compute' third- or higher order statistics - lead to his current texton theory.

2.2 Texton Theory

Texton theory, like Julesz's statistical theory, is concerned only with exploring preattentive, or non-cognitive texture processes. The fundamental distinction between the two models is that statistical texture models emphasize the arrangement of the parts of a textured scene, while texton models emphasize the nature of the specific parts. Texton theory is based upon observations that the visual nervous system appears to display certain special sensitivities to particular elements of a textured surface. Julesz and Bergen (1983) have summarized their texton theory in three heuristics:

- Heuristic 1.** Human vision operates in two distinct modes: preattentive and attentive. In preattentive mode, spatial information is processed rapidly, without scrutiny, in parallel, and covers a large visual field as in texture discrimination. In attentive vision the processing is in a serial search and involves focal attention (scrutiny) to small "apertures" of the image.
- Heuristic 2.** *Textons* are form primitives with specific spatial properties - which elicit high sensitivity to the preattentive process. They include the spatial distribution of "elongated blobs" (rectangles, ellipses, etc.) with specific colors, angular orientations, widths and lengths, terminators (end-of-line segments), and line crossings.
- Heuristic 3.** Preattentive vision is selective only of areas where texton density (numbers) differs. It directs attentive vision to these locations, but ignores the positional (spatial) relationship between textons. (p. 1662).

According to Julesz, when our attention encompasses an entire visual scene, the only areas that are instantly (within approximately 200 msec) obvious to us are those with density

differences in textons. From a neurophysiology perspective, textons, in particular the elongated blob, have a parallel in primate neurophysiology - where similar features are found to stimulate the simple neural units in the striate cortex (visual cortex) of monkeys, which are selectively tuned to elongated blobs of certain colours, orientations, width and lengths. Another important property of these cortical units is that for homogeneous stimuli, they do not fire (Hubel and Wiesel 1968 in Julesz and Bergen 1983). From a texture perspective this is important as texture discrimination initially implies heterogeneity of stimuli (Gibson 1950).

While Julesz believes textons reflect the special sensitivities of individual neurons, others (Beck, Prazdny, & Rosenfeld 1983; Uttal 1988) believe they reflect the action of vast networks of interacting neurons whose collective function is expressed in these special sensitivities. Perhaps textons, for some as yet not understood reason, are forms that best allow global structures to be created. In other words, textons may be efficient because they create a shortcut - reduce the computational or processing demand on the brain - by permitting the same sort of global perception to be used as in lower order statistics.

2.2.1 Supportive Research for Textons

Julesz is not alone in trying to unravel something general about human form perception from a visual texture perspective. Other researchers pursuing quantitative approaches to texture discrimination include: Beck, Prazdny, & Rosenfeld (1983) who describe how the elements of a textured surface could be grouped rather than being perceived as independent entities. Grossberg and Mingolla (1985) have built what they call a *boundary-contour model* that establishes boundaries between textures surfaces in a manner very similar to the human observer; and work by Triesman & Patterson (1984) also suggest that something like Julesz's primitive visual textons are responsible for generating global structures, thus reducing the computation requirements on the brain for texture discrimination.

In agreement with the texton concept but from a computer vision perspective, the important work of David Marr (1982) involves a hierarchical framework developed to derive shape information from images. The most elementary level of this framework, the *primal sketch*, involves defining *tokens* (primitives) consisting of edges, line segments, and blobs, then grouping these tokens based on the first order statistics of the token attributes e.g., token

orientation, widths, lengths, contrast, intensity levels, and spatial density of tokens or groups. It is interesting to note that early in his research, Marr assumed that the neurophysiological findings had direct relevance to vision, while Julesz and his group following an opposite path, worked for nearly two decades to find evidence for the use of simple cortical units in texture perception (Julesz and Bergen 1983).

These researchers generally agree upon three main aspects of visual texture perception. First, it is generally perceived as being a preattentive process that depends upon the interaction of the constituent local features (form primitives) of the textured surface. Second, some sort of parallel or global interaction among these features or elements exists, so that those that are perceptually similar are clustered together. Third, many of the local or specific relationships among the elements (e.g., the differences in element shapes / sizes) are invisible or unprocessed at this primitive level of visual processing. These specific relationships or organizational differences only emerge (later) when the elements are attentively scrutinized (Uttal 1988).

2.2.2 Textons describe texture, not second order statistics

Contrary to Julesz's earlier research (Julesz 1975), his recent findings (Julesz 1981, Julesz and Bergen 1983) suggest that the preattentive visual system cannot process second-order statistical parameters; therefore segregation must be based only on local density differences (a first-order difference). As a consequence, the higher-order statistical parameters like those suggested previously in the statistical model can be ignored. While a considerable amount of vision is carried out by the preattentive system, its power of information processing is limited and depends on local density differences of textons.

The concept of textons, or in Marr's language *tokens*, reaffirms the importance of primitives in texture discrimination (section 1.1). Julesz (1983) is careful not to claim that textons are the building blocks of form vision, yet he does suggest that the preattentive system instantly detects the location of texton differences - based only on local density differences - then directs the aperture of focal attention to these locations. The attentive system within its small aperture of attention (often as small as a few minutes of arc (De Valois and De Valois 1988)) would then assess, or process the spatial relationship between textons. It is interesting to note, that in this attentive or scrutiny process, the aperture of

attention changes its spatial scale (within physically defined limits) according to the size of the features being sought (due to the focusing, or resolving mechanisms of the eye). In computer vision, this would be analogous to a variable size/shaped moving window, capable of changing itself, based on the size/shape of the object(s) being analyzed...definitely a non-trivial task.

2.3 Haptics

Art thou not sensible to feeling as to sight?

- William Shakespeare (in Fu et al., 1987)

Haptics is defined as a perceptual system that incorporates inputs from cutaneous receptors, and also from kinesthetic receptors embedded in muscles, joints, and tendons (Loomis and Lederman 1986). In simpler terms, haptics involves deriving sensory information from human touch. This is commonly obtained in experiments via hands or fingers *actively* contacting a physical surface (Gibson 1962). The proceeding synopsis of psychophysical haptic literature distinguishes the three different current approaches to vision and haptic research, indicates their relative importance to form perception, and identifies the currently perceived role haptics plays in texture perception.

In 1764, Thomas Reid accurately expressed the *first* of these three approaches by claiming "*Of the five senses, sight is without doubt the noblest. The evidence of reason is called seeing, not feeling, smelling or tasting.*" (Reid 1764/1967 in Heller 1982). This vision centered approach appears strongly supported in our society by the overwhelmingly uneven distribution of investigators involved in vision research, compared to the other four human senses.

The *second* approach regards touch as a more relevant sense of 'reality' than vision. In 1749, Diderot remarked that touch was responsible for our belief in the existence of objects, and educates vision in object permanence (Diderot 1749/1972 in Heller 1982).

The *third* approach is poignantly alluded too in Judeo-Christian mythology, where the Disciple 'doubting' Thomas exclaimed "...*Except I shall see in his hands the print of the*

nails, and put my finger into the print of the nails... I will not believe." (James 20:25 - The Holy Bible). This combined perceptual approach involving vision and touch has occupied increasingly more haptic research during the last ten years (Garbine and Bernstein 1984; Jones and O'Neil 1985; Lederman et al., 1986; Garbine 1988; Heller 1989).

An excellent vision/haptic review by Klatzky (et al., 1987) indicates that many of the earlier form perception experiments comparing haptics and vision were biased toward vision. As a result many of the experiments either failed to include haptically important properties such as texture, hardness, thermal conductivity, and absolute size when depicting real objects, or they did not vary these properties when using unfamiliar forms. This specific review, and the other papers previously cited, indicate that touch primarily uses texture to judge surface properties of single, 3-D objects, where the information under each finger 'belongs' to the same object, and is used to describe surface characteristics such as roughness, coarseness, jaggedness, and less often, element density and configuration.

While studies exist that indicate vision dominance in texture/form perception (see review in Jones and O'Neil, 1985), it is not surprising to note that both vision and haptics encode texture well. Indeed, the 'real world' texture of a surface is still perceptible in the dark, where vision would fail to record any texture at all. Studies by Lederman & Abbot (1981; Lederman et al., 1986) indicate that depending upon which characteristics of surface texture observers were required to judge, the relative 'weighting' or 'reliance' between the two modalities would shift. When instructions referred merely to "texture", vision and touch weighed the inputs about equally. When instructed to treat texture as "spatial density", vision dominated, and when instructed to treat texture as "roughness" touch dominated.

In textured environments where the macrospatial distribution of surface elements is not obvious, and especially when a single object is being perceived at one time, texture perception is more likely to be relevant to haptic exploration than vision. In contrast, vision is thought to use texture variation primarily to segment the visual field into distinct objects, to judge depth, and to judge microspatial patterns within homogeneous surfaces (Klatzky et al., 1987).

CHAPTER THREE

COMPUTER VISION TEXTURE

Digital remote sensing and geographical information systems (GIS) incorporate information technologies with capabilities for storage, analysis, and display of spatial and non-spatial information (for an excellent review of RS and GIS epistemology, see Avery and Berlin 1992 and Maguire et al. 1991). The digital environment where these technologies coexist, is referred to as computer vision.

Computer vision (CV) may be defined as a research domain where technologies for extracting, characterizing, and interpreting images from a three-dimensional world occur. This domain subdivides into at least six principal areas: (1) sensing, (2) preprocessing, (3) segmentation, (4) description, (5) recognition, and (6) interpretation. Sensing is the process that yields a visual image. Preprocessing deals with techniques such as noise reduction and enhancement of details. Segmentation is the process that partitions an image into objects of interest. Description deals with the computation of features (e.g., size, shape) suitable for differentiating one type of object from another. Recognition is the process that identifies these objects (e.g., vegetation types, primary and secondary roads, dams); and interpretation assigns meaning to an ensemble of recognized objects (Fu et al., 1987).

Within CV, the ability to interpret spatial information, and the development of efficient and robust spatial representations of those interpretations are primary objectives. To accomplish these goals, CV explores both the theoretical problems of developing a better understanding of how humans perceive the world and acquire higher-level spatial concepts, and the practical problem of developing methods to 'teach' computers to 'see' (Peuquet 1988), or visualize their surroundings (see Introduction). The following sections introduce why digital texture analysis is used in the RS of forest environments, and reviews the statistical and structural approaches to CV texture analysis.

3.1 Forests, Remote Sensing and Texture

Timber shortages in several parts of the world have prompted an intensification of forest management activities world wide. This concern for forest management has been strongly recognized in British Columbia (B.C.), where forest inventories are the basis for the management of B.C's forest resources. These managed forests cover an area of approximately 52 million hectares, contain close to 8 billion cubic meters of merchantable timber, and represent over 40 percent of the country's timber supply. Inventories are reviewed on a ten year cycle using large-scale aerial photography as their primary information source, with major disturbances and harvesting activity updated using remotely sensed Landsat Thematic Mapper satellite imagery (Pilon 1990).

From the 1940's until the present, the majority of forest inventory information (e.g., forest cover-type maps which distinguish vegetation cover by age, height, species, etc.), have been identified and organized manually, requiring specialized aerial photo interpreters to invest heavily in time and labour to create accurate output. Much of this time is utilized evaluating several phenomenon of aerial photos known as *photointerpretive* or *recognition elements*. These include shape, size, photographic tone and colour, pattern, shadow, site or context, and texture (Avery and Berlin 1985, 1992). These elements may be used individually, but are most commonly employed in combinations to assist the interpreter in defining forest objects.

With the development of computer vision technology and the availability of remotely sensed multispectral satellite data, there have been numerous attempts to automate the segmentation of forest cover (Sader et al., 1989; Cohen and Spies 1992). The rationale behind automated classification strategies has ideally been to reduce the time required to create and update cover-type maps; and to meet or exceed the accuracy of classifications generated from traditional manual aerial photo interpretation and mapping techniques. Of the photointerpretive elements mentioned, only tone is employed in standard automated strategies, resulting in output of questionable accuracy (Jensen 1986; Woodcock and Strahler 1987; Avery and Berlin 1992).

In recent years, approaches incorporating ancillary information such as site, or context in the form of digital elevation models (DEM) with RS data, have been introduced into the

classification process (Strahler et al., 1978; Franklin 1989, 1991; Niemann 1991). DEM's are a digital representation of the elevation of a portion of the earth's surface, visually portrayed as connected surface models, having unique z-values over x and y (Weibel and Heller 1991). The premise behind adding ancillary data to the classification is based on the assumption that as the dimensionality of the data increases, so does the probability of increasing classification accuracy.

Like site, texture is an important photointerpretive element used by humans for the segmentation of forest scenes (Lillesand and Kiefer 1987). In digital RS, texture is considered the visual impression of coarseness (roughness) or smoothness caused by the variability or uniformity of image tone or colour (Avery and Berlin 1992), thus texture is a description of the spatial variability of intensity or tone in an image. In a digital forest scene, this variability is produced by combinations of different structural vegetation characteristics - branching patterns, crown sizes, shapes, and spatial arrangement - registering within the resolving dimensions of the sensor. After undergoing transformations based on methodology (section 3.2.2) believed to enhance the original image texture qualities (Jensen 1986), new texture images are generated. These resultant texture images can then be added to the classification process as additional logic channels, or classification can occur independently on the 'texture' images (Alparone et al., 1990; Franklin and Peddle 1990; Wang and He 1990).

3.2 Statistical and Structural Models

In the research domain of computer vision, two broad classes of texture discriminating techniques exist. They are referred to as the Statistical and Structural models. Statistical models describe texture by statistical rules governing the distribution and relation of grey tones; thus the spatial interaction between grey-level primitives is measured by probabilities. By contrast, the structural model regards the primitives - or the objects of analysis - as forming a repetitive pattern and describe such patterns in terms of rules for generating them. Formally these rules are termed grammars (Ballard and Brown 1982). One form of grammar termed a *shape grammar* involves creating high level primitives that closely correspond to the shapes in the texture. This model is well suited for describing textures where there is much regularity in the placement of primitive elements and the texture is imaged at high resolution, e.g., as in a close-up of reptile skin, or a brick wall.

In digital RS, texture analysis typically involves using statistical models rather than structural models to quantify the spatial variation of tone or intensity in a 2-D image (Haralick et al., 1973; Jensen 1986). This is partially due to early support from psychology that indicated humans were sensitive to second-order statistics (Van Gool et al., 1983; Julesz 1975); and to the difficulty in determining structural placement rules for natural scenes (Tamura 1978; Haralick 1979; Ballard and Brown 1982). For example, it is relatively simple to define a rule that describes the placement of bricks in a wall, but what rule exists that consistently and accurately describes the varying size, shape, spatial location, and arrangement of trees in a forest?

3.2.1 Texture Approaches in Remote Sensing

In RS, no singly accepted texture definition or methodology exists (Haralick 1979), resulting in a host of methods capable of producing various classification results for a single data set (Du Buff et al., 1990; Gong et al., 1992). Some of the more commonly used statistical methods are based on Fourier spectra, grey value cooccurrence matrices and difference histograms, run length matrices, spatial domain filter masks, or texture field models like autoregression or Markov random field models (Haralick 1979; Van Gool et al., 1983). Research into the statistical characteristics of fractals in texture discrimination is also being conducted (Dennis and Dessipris 1989; Keller and Chen 1989). In the RS literature (Haralick 1973, 1979; Weszka et al., 1976; Van Gool et al., 1983; Franklin and Peddle 1987; Gu et al., 1989; Gong et al., 1992), grey level cooccurrence matrices (GLCM), while not without their limitations (Gotlieb and Kreyszig 1990; Marceau et al., 1990), appear as a standard RS texture procedure designed to evaluate the spatial distribution and spatial dependence among the grey tones in a local image area.

3.2.2 Grey Level Cooccurrence Matrix Method

The GLCM method is principally a two component technique, where the internal spectral variance of pixels within a neighborhood are considered a valuable source of spatial information. The spectral variance (spread of different tonal values, or DN's - digital numbers) in an RS data set is illustrated in figure 3.1.

The first component of the GLCM technique involves describing the spatial relationship of image primitives (or tones) (figure 3.3) within a cooccurrence matrix (figure 3.4). A cooccurrence matrix describes the relative frequencies with which two neighboring pixels (grey tones), (separated by distance d and angle a), occur within a fixed sized moving window (in this example, 3 x 3 pixels in dimension), one with grey tone i and the other with grey tone j . The second part of the technique (equation 3.1) involves calculating statistics from the matrix values that describe the relative spatial relationships of the matrix elements (Haralick 1979; Gong et al., 1992). Traditionally these statistics tend to be second-order or higher (Van Gool et al., 1983). The GLCM method also requires decisions concerning a number of variables directly associated with it, which traditionally tend to be selected in an *ad hoc*, site specific fashion (Marceau et al., 1990). These include the spatial resolution, the spectral bands, the quantization level of the image (viz: the maximum number of tones in an image), the size of the moving window, the interpixel distance and angle during cooccurrence computation, and the 'texture' statistics used.

10	10	20	20	10	20	30	20	20
10	10	30	30	30	20	30	30	30
30	30	10	40	30	40	10	40	40
20	20	40	10	30	30	20	40	40
10	30	40	40	30	20	10	20	40
20	20	10	10	30	10	30	10	40
40	30	30	20	30	10	10	10	10
30	30	40	20	20	20	10	10	10
10	40	40	10	20	20	10	10	10
40	40	30	30	30	30	10	10	10

Figure 3.1 Each grid cell represents an individual pixels' relative location, its spectral grey tone (DN) value (visually illustrated by proportional grey tone increments), and its (global) spatial arrangement within a single channel of RS imagery. The darker polygons represent two, 3x3 windows.

For each moving window *view* of the data, four symmetric grey-tone spatial-dependency cooccurrence matrices (Haralick 1973, 1979) - simply referred to as cooccurrence matrices - are potentially calculable: the 0, 45, 90 and 135 degree matrices. Together, these four matrices describe the eight directions of the (nearest) neighboring cells - excluding those on the periphery of an image - that surround the central cell in a square window (illustrated in figure 3.2). In figure 3.4, a symmetric cooccurrence matrix is created that summarizes the way (figure 3.3) grey-tone elements occur (with an interpixel distance of 1) next to each other (at an angle of 0°). The angle 0°, indicates that each grey-tone is compared to its neighbors located immediately to the right, and left of its position. In figure 3.3, this matrix would be evaluated (from the top left): 10 next to 30, 30 next to 30, 40 next to 10, 10 next to 30, 20 next to 40, 40 next to 10, then in the reverse direction: 10 next to 40, 40 next to 20, etc.

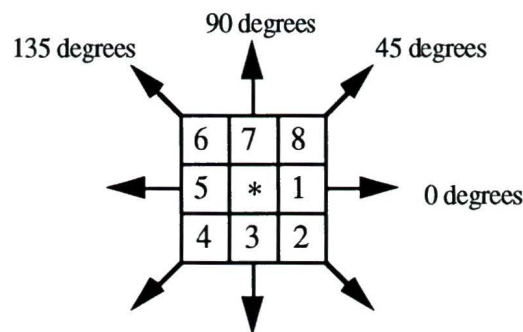


Figure 3.2 Resolution cells 1 and 5 are 0° (horizontal) nearest neighbors to resolution cell *; resolution cells 2 and 6 are 135° nearest neighbors; resolution cells 3 and 7 are 90° nearest neighbors; and resolution cells 4 and 8 are 45° nearest neighbors to *. (Note this information is purely spatial, and has nothing to do with gray-tone values.) (From Haralick 1973 p. 612.)

10	30	30
30	10	40
20	40	10

Figure 3.3 DN values within a heterogeneous window (upper left figure 3.1).

0° Matrix

	10	20	30	40	Total
10	0	0	2	2	4
20	0	0	0	1	1
30	2	0	2	0	4
40	2	1	0	0	3
Total	4	1	4	3	12

Figure 3.4 A cooccurrence matrix of values representing the spatial relationship of the DN's in figure 3.3. (30, 10) (highlighted) indicates that the value 30 occurs (with an interpixel distance of 1) next to the value 10, twice in this 0° direction matrix.

The values obtained from this matrix may then be used to create a statistical measure describing the spatial relationship of the matrix elements. Some of the more common spatial measures are angular second moment (ASM), contrast, inverse different moment, entropy, and correlation (Haralick 1973, 1979; Weszka et al., 1976). ASM is a statistical measure of homogeneity. A small ASM represents a spread of values in the cooccurrence matrix, thus a heterogeneous, or coarse image texture within the window perimeter. A large ASM represents greater homogeneity of DN's, thus a relatively 'smooth' texture (figure 3.4). An example of how the second-order statistic ASM is used to derive a texture measure is illustrated in equation 3.1, and figure 3.5. In this equation, P is the spatial cooccurrence matrix, and R is the frequency normalization constant for the selected orientation (Franklin and Peddle 1987).

$$ASM = \sum_i \sum_j \left(\frac{P(i,j)}{R} \right)^2 \quad \text{Equation 3.1}$$

$$ASM = (4/12)^2 + (1/12)^2 + (4/12)^2 + (3/12)^2 = 0.26$$

The ASM texture value 0.26, represents a relatively coarse texture, defined by the sum of the square of the spatial dependencies of a heterogeneous window (figure 3.3). When creating a GLCM texture image, the ASM value (in this case 0.26) would be derived from

equation 3.1, then assigned to the central pixel location of figure 3.3 as the new DN texture value. The window would then move over one column, and the same operation would be performed on the new matrix of values within the window perimeter, until the entire image is analyzed, and a new ASM texture image is created. This type of moving window transformation technique does not allow the edges of the original data to be analyzed. Figure 3.5, illustrates another example of DN values located within the same 3x3 window after it has 'moved' further through the (figure 3.1) data set. The cooccurrence matrix derived from this window (figure 3.6) has fewer grey tone transitions than found within (figure 3.3), therefore fewer entries, thus a larger ASM magnitude.

10	10	10
20	10	10
20	10	10

Figure 3.5 DN values within a homogeneous window obtained from figure 3.1 (lower right).

0° Matrix

	10	20	Total
10	8	2	10
20	2	0	2
Total	10	2	12

$$\text{ASM } 0.694 + 0.027 = 0.72$$

Figure 3.6 ASM values derived from figure 3.4 (by using equation 3.1). A large ASM represents a smooth, or homogeneous texture.

Once derived, the new ASM 'texture' image represents a measure of the homogeneity of the pixels comprising the data set (derived from a neighborhood search within a fixed sized window), and may be used as an additional logic channel for image classification. Typically, the averaged value derived from the four grey-tone spatial-dependency matrices (0, 45, 90, and 135) is output as the texture value for the pixel under analysis (Van Gool et al., 1983; Jensen 1986; Gong et al., 1992).

CHAPTER FOUR

PSYCHOLOGYS' INFLUENCE ON CURRENT RS TEXTURE

In chapter one, an important concept underlying this thesis was made. It stated that much of the current RS texture methodology appears premised on invalid second-order statistical vision texture theories, and that these dated ideas result in many of the present inadequacies with current RS texture methodology (section 3.2.2). As a precursor to the reasoning behind the methodology section (Chapter five), the following discussion is intended to briefly illustrate the influence that dated visual texture theory still claims on current RS texture methodology. This chapter will also review four of the previously discussed differences between human texture perception and RS texture methodology.

4.1 Texture Chronology

Premised on the pioneering vision research of Bella Julesz and his colleagues (Julesz 1962, 1975, 1978; Julesz et al., 1973) on the role second-order statistics play as descriptors of visual texture, GLCM's - originally referred to as the *spatial gray level - or - grey tone - dependence method* (SGLDM) (Haralick 1973, 1979; Van Gool et al., 1983) - were first used by Julesz (1962) in psychophysical vision texture research (Haralick 1979 p. 790). This technique was later popularized in RS, predominantly through the work of Robert Haralick. In 1973, Haralick introduced 14 texture features for use with GLCM's. It is interesting to note that of these 14 texture features, none of them are visually obvious (Tamura 1978), yet many of them, such as angular second moment, contrast, correlation, entropy, and inverse different moment are commonly used in RS today (Franklin and Peddle 1987, 1990; Marceau et al., 1990; Gong et al., 1992; PCI, 1992). In the RS texture articles cited, every researcher references the 1973, and/or the 1979 papers of Robert Haralick. Some authors even attribute the GLCM method to him (Du Buff et al., 1990; Gong et al., 1992 p.138). Julesz's 1975 vision findings are also still referenced to support the use of second-order statistics as strong discriminators of digital image texture (Van Gool et al., 1983; Gotlieb and Kreyszig 1990). Together these findings suggest the influence Haralick's work (apparently premised on Julesz's (1962) psychophysical vision theory) and second-order statistical texture measures still have on the RS texture community after 20 years.

However, more recent work by Julesz and his colleagues (Caelli and Julesz 1978; Caelli et al., 1978; Julesz 1981; Julesz and Bergen 1983), significantly modifies the original conjecture provided (by Julesz) to support second order-statistics as descriptors of visual texture. The 1981 and 1983 research claims that only density changes (a first order statistic) of form primitives called *textons* explain preattentive (or instantaneous) texture discrimination. Julesz and Bergen (1983) also indicate that preattentive texton discrimination (considered a global operation) serves as 'cues' for directing the attentive (or scrutiny) visual system to determine the positional relationship between neighboring textons located within a scale varying moveable window. This refers to the human eyes' ability to detect the different size, and shape of resolvable objects within its small aperture of attention (often as small as a few minutes of arc (De Valois and De Valois 1988)). Julesz also states, that higher-order statistical parameters can be ignored, and that in fact, contrary to his earlier conjecture, the preattentive visual system cannot even process second-order statistical parameters. While a dramatic change from his initial statistical-texture theory (Julesz 1975), support for textons (form primitives) as the basis of texture perception from other texture associated disciplines is strong: including neurophysiology (Hubel and Wiesel 1968), psychophysics haptics research (Gibson 1962; Lederman et al., 1986, Klatzky et al., 1987), psychology (Triesman and Petterson 1984; Biederman 1987), and computer vision (Marr 1982; Beck et al., 1983).

4.1.1 Human and RS Texture Theory Discrepancies.

A texture literature search indicates that by adhering to dated psychophysical texture theories, four significant discrepancies presently exist between human texture perception and RS texture analysis. These discrepancies involve:

- (1) **Primitives:** In RS texture, the primitives of analysis are individual pixels, which represent one, from many possible spatial sampling units of the same scene, modifiable at choice according to the sensor design; and which do not correspond to objects on the ground - if they did, they would vary considerably in size and shape (Marceau 1992). In human texture perception, the primitives of analysis are discrete entities, or objects that extend across pixel boundaries (Gibson 1962; Li and Strahler 1985; Lederman et al., 1986)

- (2) **Spatial Arrangement:** In RS, GLCM's and second-order statistics remain the *standard* procedure used to evaluate the spatial dimension of textures (Haralick 1979; Franklin and Peddle 1990; Gong et al., 1990); yet this form of statistical methodology - relying heavily on a fixed sized moving window (Marceau et al., 1990), and second order statistics - has recently been shown inadequate to represent human visual texture (Tamura et al., 1978; Julesz 1981). Current visual and haptic theory suggests that texture analysis occurs by a global process, defining object locations based only on density differences (a first order statistic). Scrutiny then proceeds at these locations, in the form of a moving window that changes its scale (e.g., the resolving ability of the human eye), according to the size of the features being sought, so that objects' spatial relationships may be determined (Marr 1982; Julesz and Bergen 1983; Klatzky et al., 1987; Bergen and Adelson 1988; Uttal 1988).
- (3) **Scale / Spatial resolution:** Most RS primitives are of a spatial resolution inappropriate for the extraction of object specific information (Marr 1982; Woodcock and Strahler 1987; Cohen and Spies 1992). It has been suggested that in order to detect a feature, the spatial resolution of the sensor should be less than half the size of the feature measured in its smallest dimension (Jensen 1986). Compliance with this poses its own difficulties. As the spatial resolution of a sensor increases, so does the spectral variability of surface features, resulting in a reduction of statistical separability (with traditional RS classifiers), and a consequent reduction in classification accuracy (Woodcock and Strahler 1987; Marceau et al., 1990). In human texture analysis, the physical dynamics of the eyes' resolving ability, and the tangible requirements of the haptic system to "feel" texture, indicates that texture is a scale specific phenomenon. If the objects of analysis are non-resolvable, information implicit to their structural composition is also non-extractable (Marr 1982).
- (4) **Depth:** In RS, texture is considered nearly exclusively a 2-D research topic, founded on the premise that the 3-D world is mapped onto our 2-D retinae (Julesz 1975; Marr 1982; De Valois and De Valois 1988). Yet object specific height, or depth cues (a third dimensional information source) are readily available to humans

in both monocular and stereo images, and are used for size and shape discrimination (De Valois and De Valois 1988).

Because these differences result in less than ideal RS texture strategies and output, the following methodology section has been designed with the intention of overcoming these problems.

CHAPTER FIVE

METHODOLOGY

In contrast to the statistical texture methodologies traditionally employed in RS, the triangulated primitive neighborhood method (TPN) is a structural methodology that utilizes the key characteristics of human texture perception, to discriminate texture within-stands, and at the fuzzy boundary between - two different age class forest - stands.

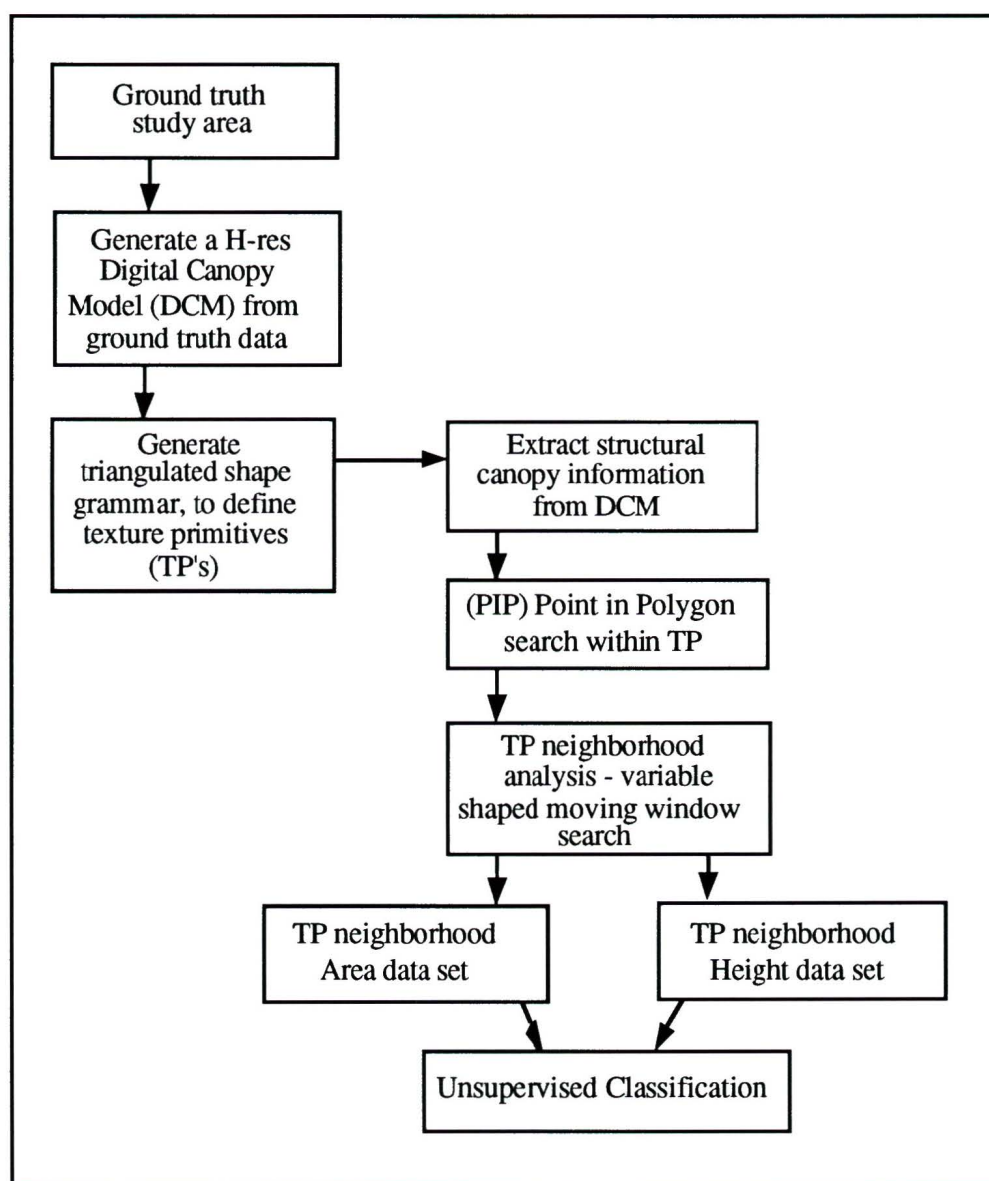


Figure 5.1 Methodology outline.

The term *key characteristics*, refers to evaluating the physical size, shape, and spatial arrangement of the components that constitute a 3-dimensional scene, so that regions with similar structural characteristics may be delineated. This evaluation will occur by (hierarchically) assessing the height and area characteristics of resolvable 3-D object specific primitives, within the neighborhood of a variable shaped moving window (section 5.5). All computer programs used to extract texture information were generated by the author in the C programming language.

From an analytical perspective, texture may be regarded as what constitutes a macroscopic region. Its structure is simply attributed to the repetitive patterns in which primitives are arranged according to a placement rule (Tamura et al., 1978; Ballard and Brown 1982). Because the trees in a forest vary substantially in size, shape, and spatial arrangement, it is impossible to create a placement rule that accurately defines a forest's spatial characteristics, without first 'knowing' the constituents that cause these specific spatial characteristics. Therefore, the varying spatial and physical attributes of the trees in a study site were initially defined by ground truthing; a global placement rule was generated that represented these object-specific spatial attributes; then structural characteristics were extracted and grouped, to represent similar textured regions.

5.1 Study Area

A 0.72 hectare study site composed of two different age-class forest stands was selected within the Sooke Watershed. This watershed, located on the southern portion of Vancouver Island (figure 5.2), at Latitude 48° 33' North and Longitude 123° 42' West, is dominated by the very dry maritime Coastal Western Hemlock biogeoclimatic subzone, though a small component of moist maritime Coastal Douglas-Fir subzone also exists.

Coastal Douglas-Fir [*Pseudotsuga menziesii* (Mirb.) Franco var. *menziesii*] is the dominant seral tree species. Due to its longevity, and the area history of repeated fire and windthrow disturbances, successional processes on any site unit rarely proceed to a climax forest. Extensive timber harvesting occurred within the watershed lands prior to 1949. At this date, the Greater Victoria Water District was incorporated and undertook management of the watershed lands which now serve as the Greater Victoria Water Supply Area. Since incorporation, detailed forest inventories have been maintained (GVWD 1992).

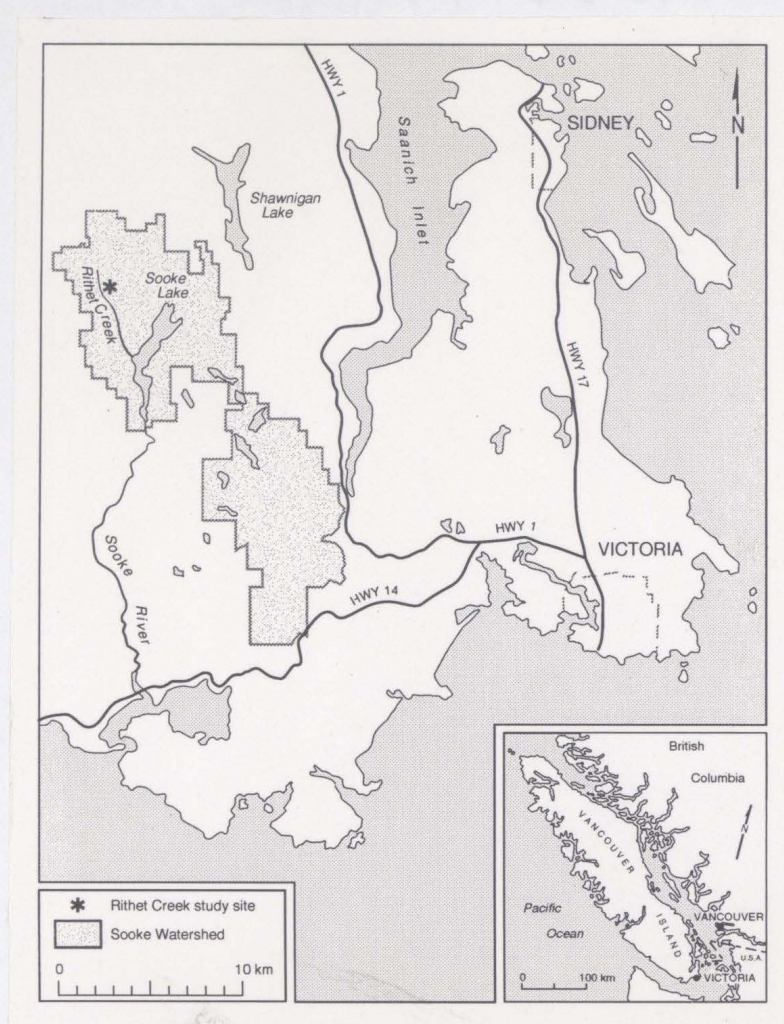


Figure 5.2 Rithet creek study site defined.

Recent (GVWD 1991) 1:10,000 forest inventory maps indicate that the forest composition of the northern study site stand (bottom of figure 5.3) is age class 2 (planted in 1965), Coastal Douglas Fir and Western Hemlock (*Tsuga heterophylla* (Raf.) Sarg); while the southern stand (top in figure 5.3) is predominantly age class 8 (141-250 yrs) Coastal Douglas Fir. Different aged stands within the same site were selected to determine the effectiveness of the presented texture methodology, to discriminate texture within-stands, and at the 'fuzzy' boundary between-stands, based on spatial data only. The test site was hand surveyed using Brunton compasses sighted along a North/South - East/West axis, and gridded with survey stakes into 72 10x10 m grid cells: 8 cells running E/W, by 9 cells running N/S. 208 tree locations within grids cells, were defined to 0.1m precision. Crown radii, diameter at breast height (dbh), species type, tree height at crown apex, and

height at maximum crown radii were also obtained from field measures using Sunnto PM-5 Clinometers, Brunton compasses, DBH tape measures, and 50 m measuring tapes. These values were then used to produce a digital canopy model (DCM) of the tree canopy surface.

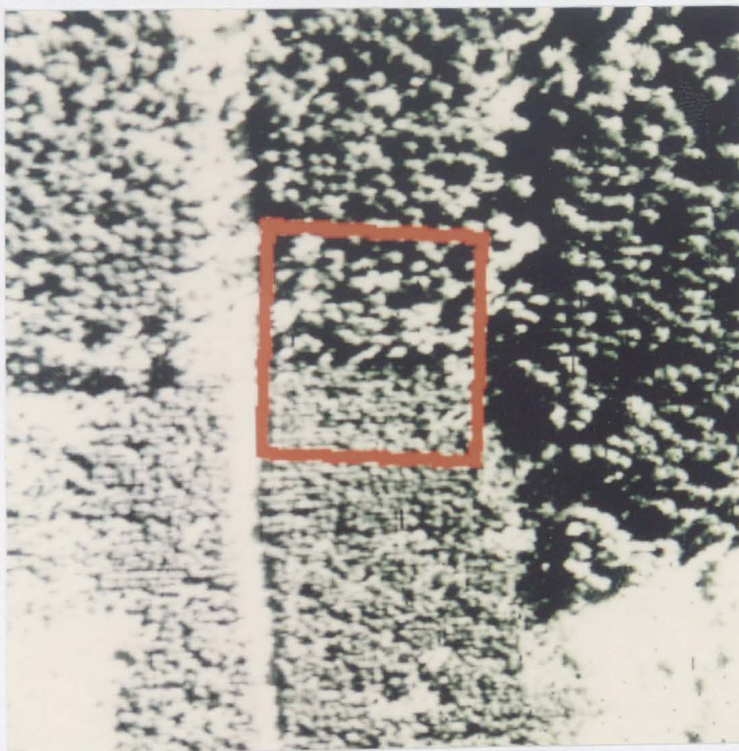


Figure 5.3 1.2 m (IR. 734.2-746.7 nm) CASI image illustrating the 2 different stands within the study site.

5.2 Digital Canopy Model (DCM)

A DCM is a H-resolution 2.5-D digital elevation model of a tree canopy surface, that visually portrays the spatial arrangement, height, and different size of the various canopy constituents (in this case individual trees) in relation to each other, and to the ground. In the 1:15 000 vertical aerial photographs, and 1.2 m CASI imagery of the study site (figure 5.3), individual tree crowns visually appear conical in shape. Groundtruthing within the site demonstrated that crown shapes ranged from near perfect cones, to rectangular and cubic. For simplicity in modeling, a computer program (*testsurf*) was created, that allowed each of the 208 object primitives (OP's) to be modeled (in plan perspective) as octagonal conics, graphically representing 80% of the maximum crown radii of each tree (figure 5.4). This value was selected due to 3-D modeling limitations within the DEM package

SURFACE III (Interactive Concepts Inc. 1992). In this environment, each OP was also visually modeled 'pencil-like' (figure 5.5), representing the height at crown apex and maximum crown radii, and the geographic location of each tree to correlate with a plan perspective of the site. In the same modeling package, the 72 study site grid cells were digitally represented as a 956*860 pixel data set, where each pixel = 0.1m²; thus the descriptor *H-resolution*. All modeled variables were based directly on field measures (Appendix 1).

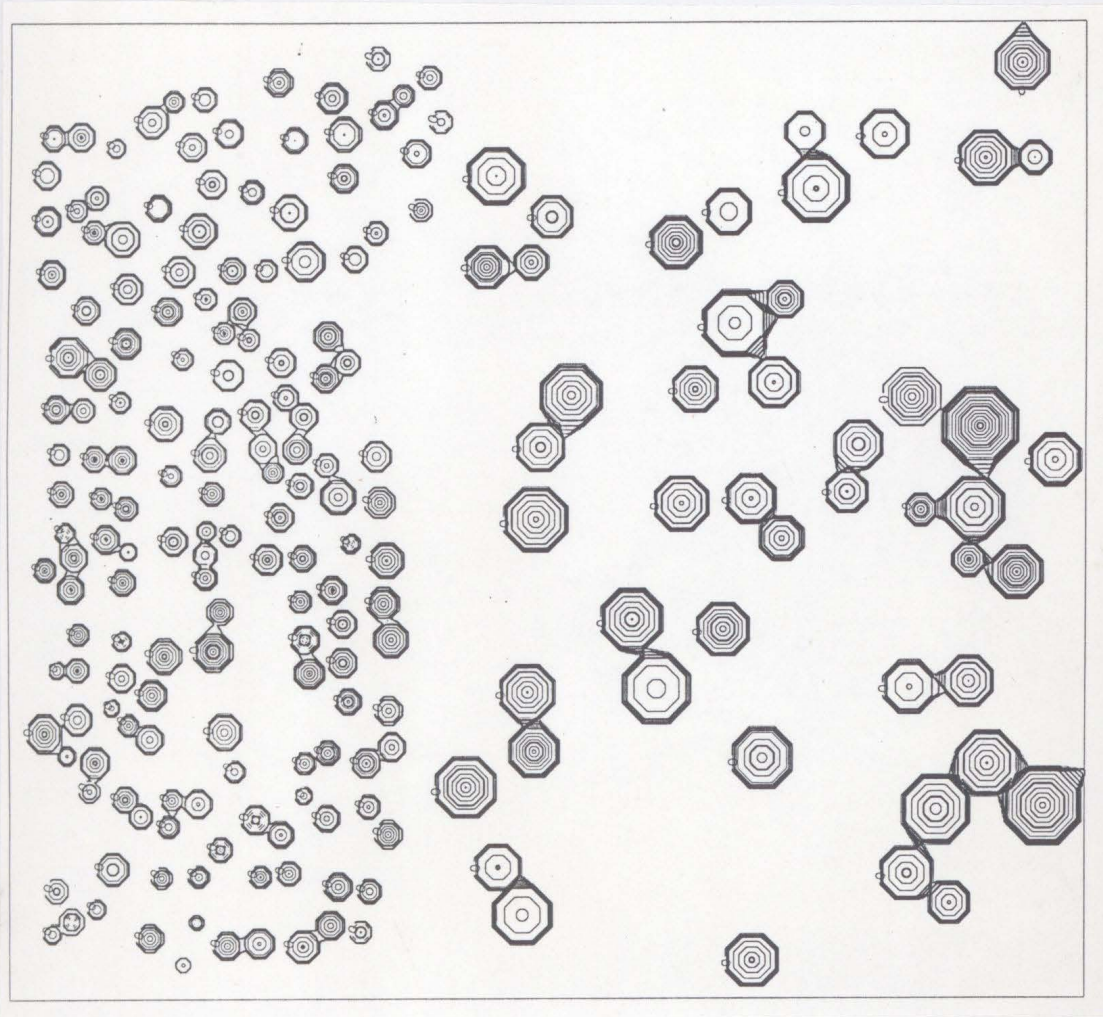


Figure 5.4 This illustration represents a plan view of the DCM study site (rotated 90° westward). The octagonal shapes visually represent 80% of the maximum crown radii, and the exact spatial location (± 0.1 m) of all 208 individual study site trees. Note, that the 'Step-like' lines adjoining several OP's are artifacts of the modeling routine. Crown contours represent 1m intervals.

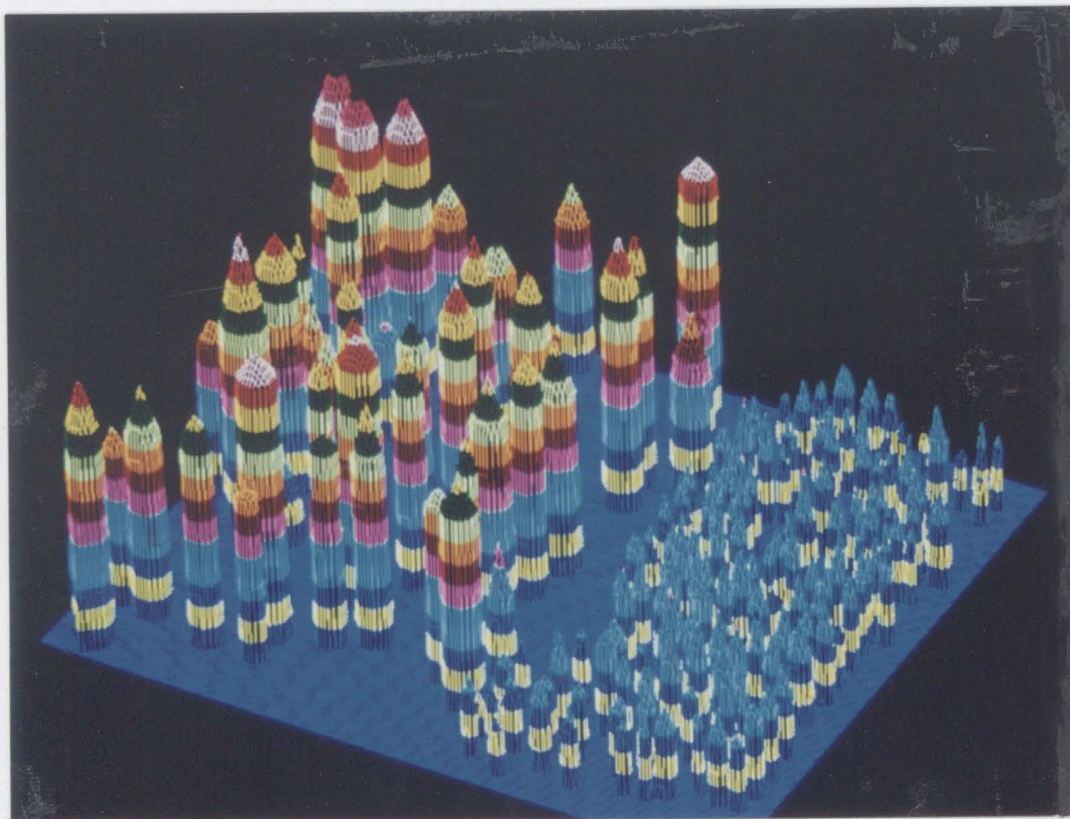


Figure 5.5 This DCM perspective of the study area illustrates the spatial arrangement, height, and different sizes of various trees in relation to each other and the ground. Different colours represent 5.0 m height intervals.

5.3 Delaunay Triangulation

Delaunay triangulation was originally developed as a contouring routine, created to determine the Thiessen neighbors - or most compact division of space - of successive points on a map. This is accomplished by forming a network of triangles as nearly equiangular as possible, and where the longest sides of the triangles formed, are as short as possible. The assumption driving this procedure relies on the positive autocorrelation of points (at least over short distances), that is; the value of a surface at one point is closely related to values at nearby points, and less closely related to values at more distant locations. The proceeding diagrams (figure 5.6) illustrate the steps involved in Delaunay triangulation (McCullagh and Ross 1980; Davis 1986; Tipper 1990).

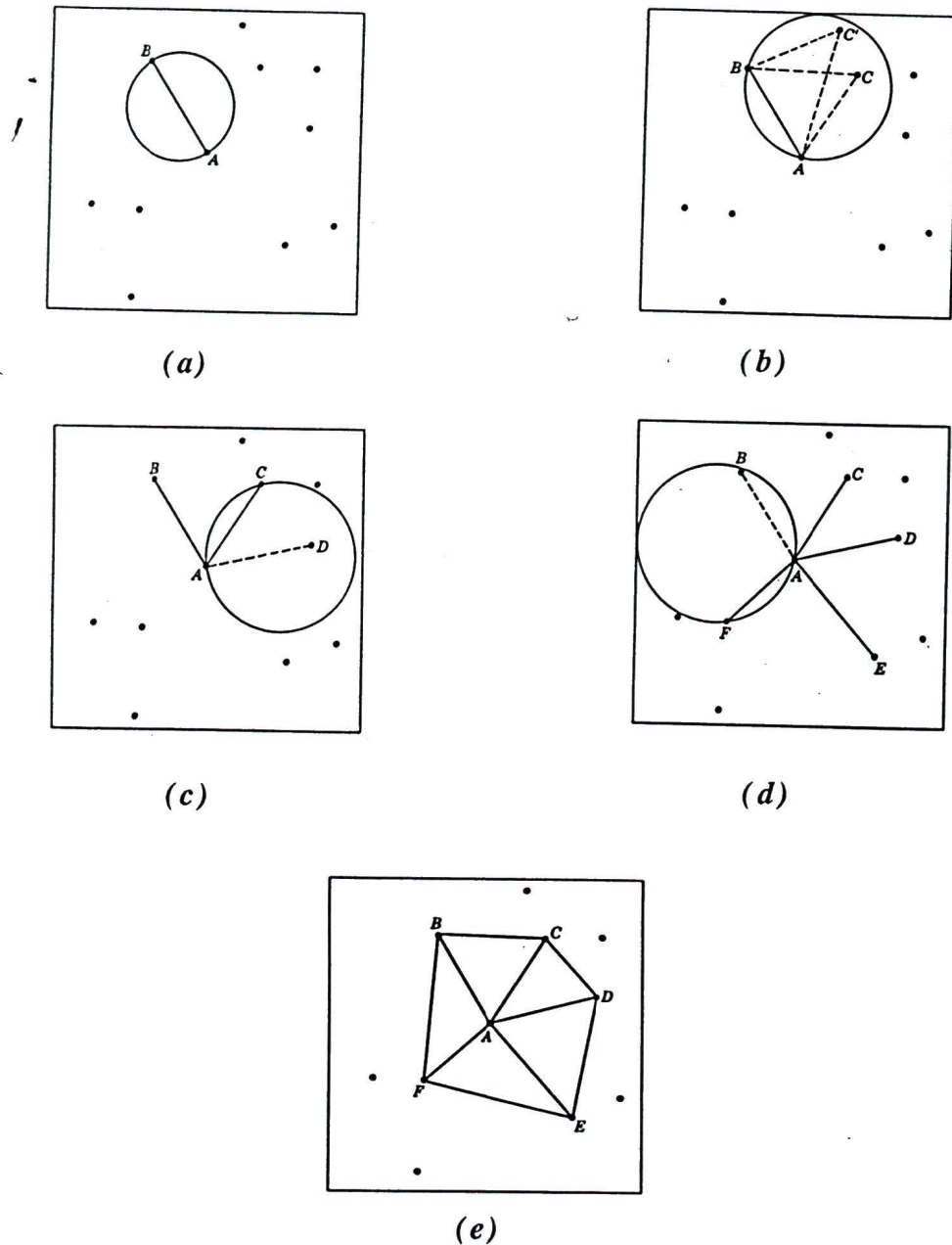


Figure 5.6 Determining the Thiessen neighbors of point A. (a) Point B is selected as a possible neighbor, and a circle with Diameter AB is constructed. If the circle contains no other points, B is a neighbor. (b) A larger circle with A and B on the perimeter is used to search for the nearest neighbor in a clockwise direction. C is the nearest neighbor, as angle BCA exceeds angle $BC'A$. (c) Circle search from AC, finds neighbor D. (d) Final circle search finds point B again. (e) Connecting the Thiessen neighbors of point A forms a Delaunay triangular network around A. The procedure then moves to one of the points B-F and begins again. (from Davis 1986 p. 360-1).

5.4 Texture Primitives

Based on visualization experiments (conducted by the author), and the premise that it requires at least 3 points on a plane to create a region (figure 5.7), Delaunay triangulation (representing a global operand) was employed as a shape grammar (section 3.2) to regionalize the study site surface. Triangulation was conducted using the software package EMXS (Sundance 1992), where 36 additional periphery points - representing 10 m intervals around the site boundary - were incorporated into the data set to be surfaced with the central crown locations of the 208 study site trees. This combined data set yielded 452 topologically defined triangular elements, referred to as texture primitives (TP's). The additional points were required to 'tie' the DCM to the (modeled) surveyed site boundary, and the term *topology* indicates that each triangle has a record of, or can spatially identify the location of itself, with regard to its neighbors.

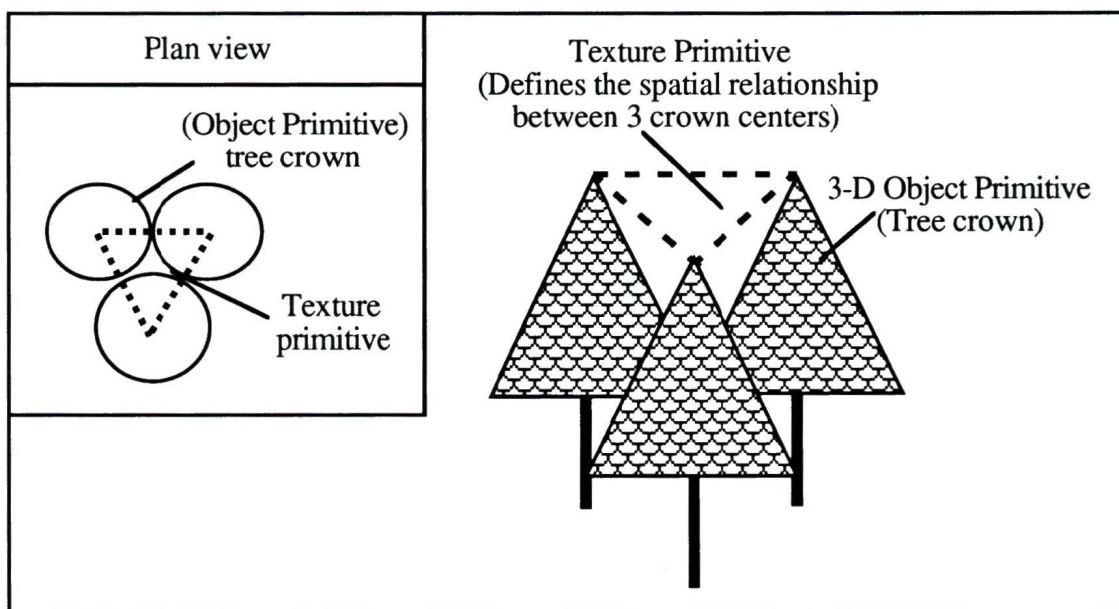


Figure 5.7 Object primitives (OP's) and Delaunay triangulation texture primitives (TP's)

5.5 Extracting Structural Information

TP's visually represent the unique spatial arrangement and density differences among all trees in the study site. Structural information relating to the portion of 3 trees located within each TP (figure 5.8) - such as tree height, and area - may be individually extracted (from the background in the case of tree height data), by a point-in-polygon search (*PIP* in

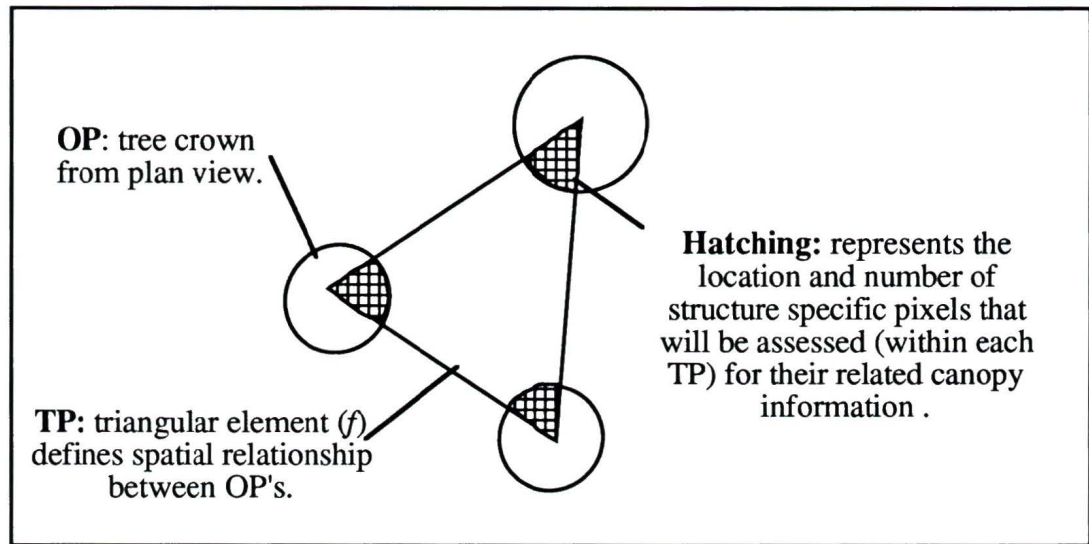


Figure 5.9 OP canopy information defined. Hatching represents individual pixels containing canopy specific structural information that will be assessed.

2. Once the pixels that constitute the OP's have been determined to reside within f , extract these n pixels' z (height) information, sum them, divide by n , then assign this averaged crown-height to the z value of all pixels residing within a new data file - but at the same (x, y) coordinates as those the information was derived from in f .
3. Repeat this process for a different TP and its associated OP's until the entire data set has been evaluated, and the transformed results stored in a new file. This procedure effectively normalizes each TP based on the object specific height/crown area (which could be equated to an estimate of *size*) of the portion of the trees located within its perimeter.

In this study, texture involves describing the spatial arrangement of the 3-D components (x , y , z) that constitute a surface. The completed computations (PIP) define how *select* portions of each tree within a TP 'interact'. They do not described how *all* tree portions within each TP interact with their neighbors. To accomplish this, further analysis is required.

5.5.1 Neighborhood Analysis

After assigning PIP data to TP's based on a single structural characteristic - such as height, or area - the program *Neighbors2* (Appendix 2) creates a variable shaped, moving 'window' which selects an initial TP as the object of analysis. This selection is followed by a topological search to locate this TP's immediate neighbors (section 5.4). Once

neighbors are located, their combined Neighborhood 'structural' information is averaged, and assigned to the initial TP (figure 5.10). Averaging serves as a representative evaluation of the immediate spatial environment, where the interaction of all portions of the 3 OP's is quantified. The object-specific window then moves to the next TP until the entire data set is analyzed and the transformed window results are saved as a new Neighborhood data set. Averaging occurs by counting the unique TP's that share at least one common vertex summing their individual structural data values, then dividing this summed value by the number of neighboring TP's (including the locus TP).

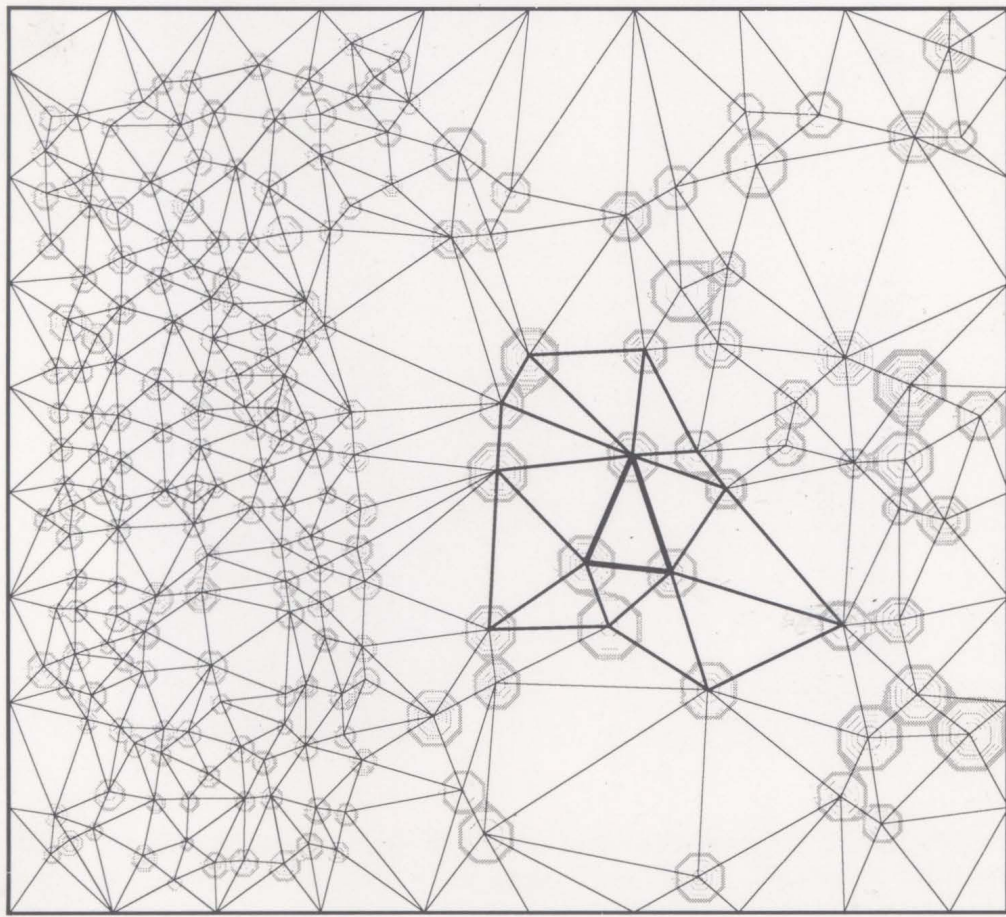


Figure 5.10 Within the TP neighborhood (defined by dark triangular boundaries), canopy structure information assigned to neighboring TP's is averaged, then reassigned to the central TP. This results in a representative evaluation of the immediate spatial environment where all portions of the 3 trees interact.

The moving window routine results in an evaluation of a single structural canopy characteristic, where *all* portions of the trees constituting a single TP interact with their neighbors. The two data sets created and evaluated in this study are Neighborhood Area

(figure 5.11), and Neighborhood Height (figure 5.12). Neighborhood Area is simply a measure of the average area within each TP Neighborhood. Neighborhood Height is a measure of the average height per crown unit within each TP Neighborhood. TP area is a strong structural discriminator of differing crown densities: dark toned TP's represent three trees interacting in a small neighborhood area, thus a high crown density. Bright toned Texture primitives represent three trees interacting in a large neighborhood area, thus low crown density.



Figure 5.11 TP Neighborhood data sets were imported into PCI (1992) software where they were linearly transformed to 8 bit data. This figure illustrates the results of an unclassified neighborhood analysis on TP area data displayed using PCI software. Bright tones represent areas of low crown density, dark tones represent areas of high crown density.

PIP is designed to allow the extraction of one height parameter - the average height per crown area of all pixels representing tree crown data within a single TP (section 5.5.1) - and three area data types: (1) the tree crown area only, (2) the non-tree area only, and (3) (as used in this analysis) the total 2-D area within the perimeter of each TP. The

combination of triangulation, PIP, and Neighbors2 routines will be referred to as the triangulated primitive neighborhood method (TPN).



Figure 5.12 TP Neighborhood data sets were imported into PCI (1992) software where they were linearly transformed to 8 bit data. This figure illustrates the results of an unclassified neighborhood analysis on TP height data displayed using PCI software. Dark tones represent low average neighboring crown heights. Bright tones represent high average neighboring crown heights.

5.6 Classification strategy

The objective behind this classification was to describe texture as a measure of the height and size of the 'interacting trees' within an area (TP) surrounded by neighboring trees (TP neighborhood). The 'interacting tree' data would then be compared for similarities that could be used to segment regions based on the similar physical and spatial characteristics of its constituents. Sections 5.1-5.5 have described the methods developed to create these neighborhood data sets. Rather than trying to describe the 'texture' characteristics of the trees in a stand with a single variable, it was considered more accurate to classify objects in 2-D data space, based on their neighborhood height/size, and neighborhood areas, within

defined spatial boundaries (TP's). By performing a 2-D scatterplot on the neighborhood area (figure 5.11) and height (figure 5.12) data sets, natural groupings in the data may be defined (figure 5.13). Four extremes represent the range of object primitives (trees), and their spatial arrangement within site boundaries.

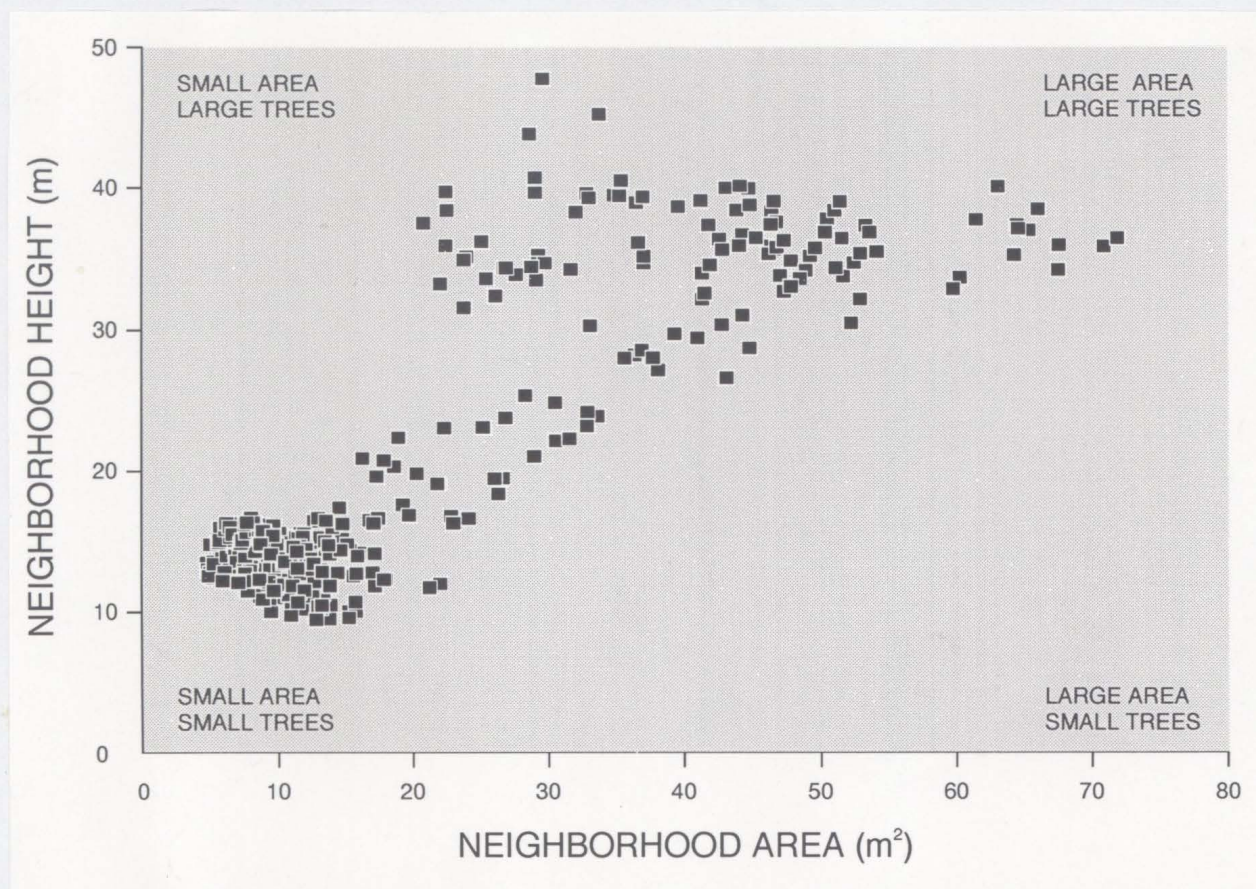


Figure 5.13 The Neighborhood Height & Area Scatterplot illustrates the natural groupings of the data, and the four extremes.

- | | |
|--------------------------------|--------------------------------|
| 1. Large trees in small areas. | 3. Large trees in large areas. |
| 2. Small trees in small areas. | 4. Small trees in large areas. |

By selecting 4 cluster centers, which correspond to the 4 possible extremes in the neighborhood height and area data sets, an unsupervised classification was performed using *k*-means clustering (figure 5.14). Four different tones in a classification scheme are defined in figure 5.14. Each tone represents regions of similar texture based on the evaluated structural characteristics of the canopy constituents. The age class 2 stand (on the left) is represented (on the left) in black. The age class 8 stand (on the right) is represented in white and pale green, with the fuzzy boundary between the two stands represented in olive.

From a spatial perspective, the classification may be evaluated in the following manner. The colour black represents small trees in small areas, olive represents large and small trees interacting together, pale green represents large trees in relatively large areas, and white represents large trees in very large areas. Classification results are more readily visible in figures 5.15 and 5.16, where both within-stand, and between-stand textures appear to visually correlate with human perceptions of the 3-D surface. In these figures, the age class 8 stand (on the right) is represented in pink and grey, with the fuzzy boundary between the two stands represented in grey-blue.



Figure 5.14 Classification results obtained by performing k-means clustering on neighborhood height and area data sets. Four cluster centers were specified corresponding to the 4 extremes defined (figure 5.13). Black represents small trees in small areas, olive represents large and small trees interacting together, pale green represents large trees in relatively large areas, and white represents large trees in very large areas.

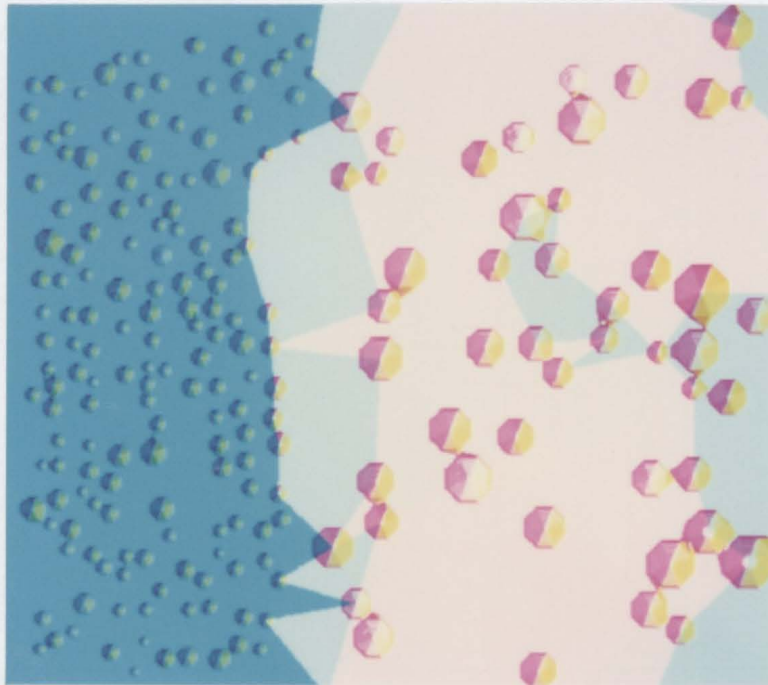


Figure 5.15 Enhanced classification results (of figure 5.14) indicate regions of similar texture, with tree locations visible. Both within-stand and between-stand textures appear to visually correlate with perceptions of the real world surface (figure 5.3). In this graphic, the white class - representing large trees in very large areas - is not individually distinguished but appears combined with the pale green class - large trees in relatively large areas. This is an artifact of the photographic medium, not of the enhancement or classification process.



Figure 5.16 This 3-D perspective (created with PCI (1992) software) visually portrays the increased discrimination available to the classified image, by using height and area data when applied to spatial specific object primitives. Regrowth (age class 2) areas appear in green, "old growth" (age class 8) in pink/orange, and the fuzzy boundary in light blue between both stands. This perspective may be located in figure 5.15 by viewing from the top middle of the image, to the bottom middle of the image.

5.6.1 K-Means

The k-means procedure, developed by McQueen (1967, in Davis 1986), is one of the most widely used clustering methods, and can be used in both supervised and unsupervised classifications. In this procedure k points characterized by m variables are designated (either by the user, or arbitrarily by the program), as initial cluster "centroids". A matrix of similarities between k "centroids" and n observations is calculated, and the closest or most similar observations are clustered with the nearest centroids. New centroids are then calculated and the process iterates through the dataset until every point has been categorized. Cluster analysis provides a relatively simple and direct way to classify objects, and presents results in a manner that are both familiar and easy to understand.

Chapter Six

RESULTS AND DISCUSSION

This chapter will address the importance of height information; some of the differences between GLCM's and the triangulated primitive neighborhood method (TPN); the scale specific characteristics of texture; why the TPN method constitutes a description of texture; the differences and similarities between pattern, texture, and contexture; and the importance of a variable size and shaped moving window for texture analysis, concluding with a discussion on techniques to potentially derive height from spectral data that would allow the TPN method to be used with current H-resolution multispectral forest imagery.

6.1 The Importance of Height Information.

To avoid many of the problems associated with assessing remotely sensed imagery (such as shadow, topographic, atmospheric, and geometric distortions) caused by differences in the geometry and reflectance of the visible surfaces, the illumination of the scene, and the viewpoint (Marr 1982), the primary data set used for analysis in this research - the DCM - was designed and generated directly from precise field measures (section 5.2). Of the field data obtained, height is the most important attribute underlying the TPN method (see Chapter 5). Within this methodology, each TP employs as its locus, the geographic location of the crown apex - representing the highest part - of each tree. Without these object specific point locations, the TPN method cannot be employed. By using height data, a hierarchy of primitives can be created where each higher primitive becomes more shape oriented, resulting in a reduction of the spatial variation of the data set as whole, and an increase in the DN separability of the data. This allows traditional clustering algorithms to be successfully used on the H-resolution DCM data set, which in past experiments have resulted in poor classification accuracies (Woodcock and Strahler 1987; Marceau et al., 1990)

The hierarchy of primitives that exist in the TPN method include:

1. Volumetric primitive: represented by individual DCM voxels (3-D pixels), these primitives are composed of spatial information in x , y and z dimensions. In the

case at hand, each of these primitives is a cubic voxel (with dimensions equal to 0.1 m) analyzed from the ground level to the upper canopy surface. The utility of volumetric primitives is that they may be used to represent object primitives.

2. *Object primitive*: these are 3-D irregularities viewed as protuberances from a base surface. In the case at hand, object primitives are individual trees graphically appearing as octagons in plan view, or 'pencil-like' in perspective view. The base surface is represented by the ground level i.e., the forest floor.
3. *Texture primitive*: TP's two-dimensionally define the spatial relationship between object primitives. Typically a TP defines an areal or regional facet (e.g., a triangle) that can be assigned the associated structural neighborhood attributes of the OP's that define its boundary. Note that the (triangular) facets taken together produce a surface with a one-to-one correspondence to the underlying base surface.

6.2 GLCM vs. TPN method

Webster's Dictionary (G. & C. Merriam Co 1976) indicates that the term texture is derived from the Latin *textura* to weave. By definition, *texture is something composed of closely interwoven elements; it is the structure formed by the threads of fabric*. With this information as a guide, one of the principle objectives of this research has been to analyze the closely interwoven elements, the three dimensional threads, or the underlying physical objects that in unison 'weave' the texture of a forest. This analytical approach involving the identification and analysis of the realworld objects that 'cause' surface texture, is the principal difference between the TPN method, and other digital texture methodologies that evaluate non-object related thematic pixels.

The author notes, that each level or scale of surface texture can be described by a lower level of elements which - analyzed as a group or region - grossly describe the surface texture. Individually, these elements - referred to as object primitives - are often an entire magnitude smaller than the surface they describe. For example, the texture of cloth may be described by the threads that compose the weave. The texture of an individual thread may be defined by the mass fibre strands that compose it; but it seems unreasonable to define the texture of cloth by the individual fibres that compose the threads. The spatial attributes of

the fibres describe only individual thread composition, they do not directly describe or represent how the threads spatially interact to form a woven cloth surface. It is almost as if a discrete plane of existence prevents such a direct description from occurring. Similarly, the texture of a forest cannot be described by the leaves and needles on trees, as they in no way describe the immediate spatial relationship of trees in the forest. They only describe the foliage in a single crown. Therefore, trees (defined by a representation (the DCM) of their perceptible canopy structure) are the object primitives of analysis in the TPN method, vs. analysis of individual pixels as used in the GLCM method.

Other similarities and differences exist between the GLCM method, and the TPN method. The TPN method reduces many of the decisions required by the analyst to create a 'texture image', making it more applicable for automated image analysis. The reduced decisions include not having to select the quantization level of the image, the size of the moving window (since it varies in 2-D shape and size as the TP's vary), and the interpixel distance and angle required for cooccurrence computation (as cooccurrence computation is no longer used). Decisions regarding which statistics to choose that best define the spatial relationship of the window elements are also reduced, as recent visual texture theory (Chapter 2) indicates all measures should be first-order. The statistic employed in this study to describe the structural and spatial characteristics of OP's, was the *average* of neighboring TP values, as the author's experience indicates similar processing occurs in human photointerpreters.

An appropriate spectral band still requires selection by the interpreter, as does the spatial resolution of the original data set. A simple heuristic to follow for spatial resolution selection, is that as a maximum, the spatial resolution of the data should be defined by the smallest sized object of analysis. Jensen (1986), suggests that in order to detect a feature, the spatial resolution of the sensor should be less than half the size of the feature measured in its smallest dimension, thus H-resolution data sets only. While analysis of these data sets will increase computation time, it is believed that the new generation of sophisticated computer hardware and software will significantly reduce this problem. The program PIP, and Neighbors2 are relatively slow, clocked on the RISC 6000 system, model 550, at 45 and 56 minutes respectively (this system provides processing speeds of approximately 57 million calculations per second). A refinement in these programs to search specific areas

instead of searching the entire data set, pixel by pixel will undoubtedly reduce their computational time significantly, to less than 5-6 minutes each.

There are several other differences in this system compared to GLCM's. The TPN method requires periphery points to 'tie' the TP's to the boundary of the analyzed data (section 5.4). These locations can easily be incorporated within the computer program PIP based on the spatial resolution of the data set. Unlike most moving window algorithms that are unable to analyze the $n-1$ pixel deep edges of the data set, [where n = either the x or y dimension of an odd numbered pixel window (e.g., 3×3 pixel window, where the first transformed value would be assigned to the central pixel location (2, 2) see section 3.2.2)], the TPN method is able to analyze pixels directly to the edges of the data. It should be noted that not all TP's bordering the edges of the data set will consist of data describing the neighborhood interaction of three trees. Some may only represent one or two trees interacting with neighbors. In two cases out of 452, the TP's are artifacts of the points input to 'tie' the TP's to the perimeter of the data (figure 5.8 top left, and bottom right TP's). While no OP specific data can be assessed from them, their existence - that is, the *area* they define - is still evaluated and adds to the unique textures of this data set.

The GLCM method involves several important advantages not present in the TPN method. The notion of 2-D pixels as objects is far more familiar and easier to work with (in a CV environment), than is the idea of 3-D variable sized and shaped location-specific primitives. Twenty years of research and application in many different image processing fields, has generated an abundance of specific literature and functioning software; and GLCM's have successfully been used and evaluated with a variety of digital imagery of realworld scenes, not just fabricated environments (e.g., the DCM). In contrast, the TPN method has still to be evaluated with a (realworld) spectral data set, and further research is required before application ready software can be created.

6.2.1 The Scale Specific Characteristics of Texture

Though some researchers believe texture involves a scaleless quality (Dennis and Dessipris 1989; Keller and Chen, 1989), the physiology of the human eye suggests otherwise. The physical dynamics of the spatial aperture (of the human eye), indicate that the OP being analyzed must be of a sufficient size to 'fit' within the 'window' or aperture of attention.

That is, to determine the visual texture of a surface, the objects that constitute it must be resolvable; consequently, texture is a scale specific phenomenon, where the scale required for analysis is determined by the size of the objects being scrutinized. The texture of the trees in a stand is hardly the same as the leaves composing a single tree crown, or the chloroplast cells in a single leaf. As the resolvable objects of analysis change, the perception of texture also changes because the surface being scrutinized differs. This is aptly illustrated in figure 6.1 where surface texture (ideally composed of constant sized OP's) varies with an apparent change in scale. In nature, scales of phenomena are not arbitrary, but tend to concentrate around discrete states as a function of the physical laws that dominate at each level (Klemes 1983 in Marceau 1992).

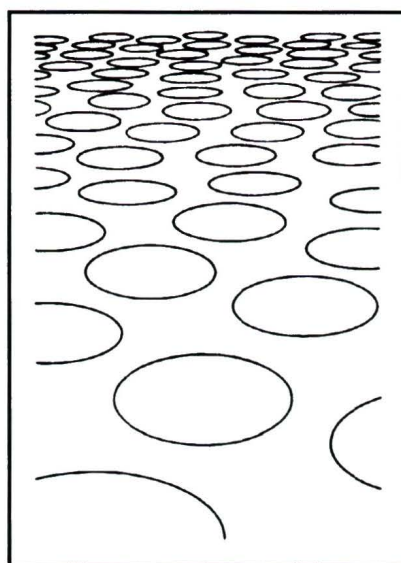


Figure 6.1 2-D *texture* elements tend to be perceived by humans as if they exist in 3-D (from Ballard and Brown, 1982 p.168).

In GLCM's a scaleless phenomenon - unrelated to the texture of realworld objects - appears definable: If the individual DN values within a window were to respectively increase by a factor of n ($0 < n < \infty$) the GLCM method produces the same statistical texture descriptor for the original values as it would for the incremented values. If this were reproduced for a realworld texture, where each pixel represented an object, and the DN value assigned to each 'object' represented the individual objects (pixels) height, then an n -fold increase in the height value (assuming n results in a significantly perceptible difference, and the scale of the measuring device is held constant) would result in a significantly different visual and haptic texture than the original textured surface.

6.2.2 Texture Described by the TPN method

The author is of the opinion, that the TPN method adheres to current human texture theory (Chapter 2) by employing methodology analogous to the processes involved as humans preattentively, and attentively analyze the texture of a 3-D surface. PIP evaluates the data generated by a global process (Delaunay triangulation) that visually represents the geographic location and density of form primitives (trees). Neighbors2 represents the attentive, or scrutiny system by extracting the 3-D object specific structural data within small apertures of the image (from the texture surface), which like the human visual system take place within a variable size/shaped moving window (section 2.2.2) and results in the creation of neighborhood data sets.

Neighborhood Height and Area data sets individually, and in unison, represent strong structural characteristics of their respective canopy constituents. While the world is no more composed of triangular elements (TP's) than it is rectangular rasters, each non-edge TP visually defines the smallest possible area between the centers of three trees; and each TP vertex represents a tree's geographic location. The Neighborhood Area data set (figure 5.11) is a strong discriminator of the average crown density of the three OP's and their immediate neighbors within each TP boundary. Dark areas indicate trees in small areas, thus a high crown density. Although this data set describes nothing about the crown diameter of the trees within each TP, experience with this forest environment indicates a high positive correlation between large crowned mature trees (age class 8), in large areas (thus low crown density), and smaller crowned young trees (age class 2), in small areas (thus high crown density).

The Neighborhood Height data set (figure 5.12) may be correlated to the *size* of the canopy, without any implicit inference to crown density. Essentially, it is a measure of the average tree height per canopy area of three trees, and their common neighbors within a TP boundary. Experience in this site also indicates a strong positive correlation between crown diameter and height - or overall tree size. When Neighborhood Height and Area data sets are combined and evaluated, they provide a description of the height (*z*) per canopy area of three trees (and their associated neighbors) within the smallest possible - or most dense - geographic areas (*x*, *y*). Based on haptic and visual theory, this is analogous to quantifying the physical size, shape, and spatial arrangement of the components that

constitute a 3-D scene (Chapter 1). As such, the TPN method is capable of determining the texture of a physical surface, that strongly correlates to the visual perception of the same scene, made by a human interpreter (figure 5.15 & 5.16).

6.3 Pattern, Texture, or Context?

In pattern recognition theory, a loose hierarchy of terms and general definitions exists. The generality of the definitions often leads to confusion in the literature. Pattern is the broadest underlying term, typically considered the spatial arrangement of natural or constructed objects (Gu et al., 1989). It describes the traits, acts, or other observable features characterizing an object; where the term *observable* is not restricted to vision. At a lower level in the hierarchy, texture, though poorly defined typically represents a measure or description of the 2-D spatial interaction of grey-tones in an image. More accurately this should be defined as *2-D image texture*, as it has little in common with human texture perception. Next comes context. In the literature this is an extremely imprecise term frequently used in conjunction with texture (though the author cannot recall seeing it specifically defined in the texture literature), as illustrated in this example where the GLCM method is specified as a methodology describing "...the texture-context information of an image..." (Haralick 1973 p.612). As an independent branch of the pattern analysis hierarchy, the 3-D object oriented texture approach - referred to as the TPN method- would reside independently from traditional 2-D texture analysis. Ideally this method describes texture as the interaction of similarly sized, shaped, and spatially arranged object primitives that constitute the perceptible haptic and visual structure of a 3-D surface.

Premised on human texture theory findings, the author stresses the necessity for the three dimensional structural and spatial characteristics of elements to be evaluated, before a description of realworld texture can be made. This has been met in the TPN method by grouping a combination of similar structural neighborhood height (z) and the area (x, y) characteristics of neighboring trees. Yet each of these Neighborhood data sets *individually* constitute strong *2-D image texture* descriptors of forest structure. While the author would argue that a combination of height and area (a 3-D) analysis is required to describe realworld texture, he is of the opinion that any appropriate 2-D structural neighborhood dataset (generated by the TPN method) can be considered a 2-D image texture measure, and may be of value in image classification.

6.4 Why a Variable Shaped/Sized Moving Window.

A study by Marceau et al. (1990) indicates that as much as 90% of the classification variability in an (texture) image, is accounted for by the (GLCM) window size, which in current RS texture methodology remains fixed. In the past, techniques used to derive window size, inter-pixel distance and angle, during cooccurrence computation have been somewhat *ad hoc* (Haralick 1979). In the study reported by Marceau et al., (1990), as many as 70 different texture bands, 4 different second-order statistics measures, and 7 different window sizes ranging from 5x5 to 49x49 pixels were experimented with, to determine which combination produced the most beneficial results; though this type of extreme rigor is seldom practiced by all researchers. Recent studies employing semivariograms are being experimented with to determine the 'best' custom window size, based on defining the maximum variance within an image (Woodcock et al., 1988 a, and b; Franklin and McDermid 1993). But to date, the primitives of analysis in RS remain individual pixels of fixed size and shape, that do not represent the realworld objects of analysis; and (unlike the variable resolving ability of the human eye), the digital window size - considered the most important characteristic of GLCM analysis (Marceau et al., 1990) - is still of a fixed dimension. To the best knowledge of the author, this thesis describes the first RS texture analysis technique, developed to use a variable size and shaped moving window that 'adapts' to resolve (and assess) the data of varying shaped object specific primitives, within uniquely shaped neighborhoods.

6.5 How to Derive Height Data from Spectral Imagery.

The TPN method may produce exceptional results for the rare study where forest inventory characteristics of trees in a stand are individually derived, but presently offers no operating method to extract height from spectral imagery (this problem is presently being addressed by the author). Current RS methodology also offers limited suggestions for automatically extracting height information from traditional spectral imagery. Indicative of this, Besl and Jain (1985) refer to spectral data as being composed of rectangular arrays of numbers, indicating the brightness at individual points on a regularly spaced grid (e.g., figure 3.1) but containing no explicit depth perceiving information. While more recent RS forest studies using CASI and MEIS data (Franklin and McDermid 1993; Gougeon 1993) indicate promise for estimating height from supervised classifications, the problem of automatically

deriving height information from spectral imagery still exists. Stereo MEIS imagery is available, but the high cost of image acquisition limits its availability.

6.5.1 Lidar

One possible method to obtain height information from spectral data involves using lidar (Light Detection and Range): pulses of laser energy (traveling at the speed of light, 3.0×10^8 m/s) in a narrow beam to the environment. The elapsed time between transmission and return is a measure of the distance between the transmitter and contacted objects in the scene (Chu et al., 1990). If flown in an aircraft, lidar produces measurements as a continuous line or profile of a narrow strip of ground traversed by the vehicle (Blair, et al., 1990). The principle drawback with current lidar technology is the inability for the profiling laser to profile each tree (under its flight path) along its crown apex (Aldred and Bonnor, 1985), resulting in an inability to define the location and height of the crown apex of each tree, thus making it insufficient for TPN modeling.

6.5.2 Pit's, Peaks, DEM's, and Future Research

The detection of topographic structures in digital imagery is not a new idea. A review by Watson et al., (1985) indicates a wide variety of techniques used to describe pits, peaks, ridges, and ravines etc. While these techniques do not describe the explicit height or shape of surface constituents, general form is perceptible. For example, if a peak shape exists on a digital surface, this indicates at least one point (with a definable location) in the image is a relative maximum, while all the points on the surface near the peak monotonically decrease away from it. Based on this idea, and the assumption that humans tend to relate texture elements of varying size to a plausible surface in three dimensions (Gibson 1950) (as illustrated in figure 6.1), the CASI spectral data of the Rithet study site (figure 5.3) - devoid of specific height information - was experimented with in a DEM environment (PCI 1992).

Figure 6.2 was generated by using 1.2 m CASI data as both the height (IR: 734.2 - 746.7 nm) and spectral drape (red: 675.1 - 685.9 nm and IR). This image offers the visual perception of tree crowns (real world objects) being isolated from each other and the ground as the DEM program associates the brightest DN's (tree tops) with the highest

elevation, and the darkest DN's (shadow) with the ground. Similar mechanisms appear to be used by human interpreters analyzing an image.

Research is presently being conducted into automatic individual tree identification from H-resolution MEIS images (Dr. Francois Gougeon, pers comm.). The developed procedures provide individual tree isolation, and the immediate extraction of their geographic positions and crown areas. Tree heights may also be obtained from stereo image pairs (Gougeon 1993; Pinz et al., 1993). In tree isolation procedures, the brightest pixel in the H-resolution MEIS data sets (40 cm) are assumed to represent the crown apex of coniferous trees as this portion of the tree is the most directly lit, and less likely to contain any shaded areas. It is important to note, that while the image (figure 6.2) appears to be composed of trees, it is possible that the brightest pixels may be the result of some highly reflected non-forest objects e.g., roads, rocky outcrops, bare ground.



Figure 6.2 In this perspective view of the Rithet study site (figure 5.3), 1.2 m CASI data is used as both height (IR: 734.2 - 746.7 nm) and spectral channels (red: 675.1 - 685.9 nm and IR), resulting in the visual perception of tree crowns (real world objects) being isolated from each other and their background.

As a continuation of this research, the author intends to further refine and develop the TPN method so that prior to triangulation, a routine will automatically scrutinize a H-resolution coniferous forest data set searching for local maxima (peaks). Under the appropriate spectral masking techniques, these maxima will ideally represent the crown apex location of individual trees (Francois Gougeon, pers comm; Gougeon 1993; Pinz et al., 1993). Defined crown locations, and object specific height estimates (derived from stereo imagery) would then allow TP's, and TP neighbors to be constructed. During the summer of 1993, stereo MEIS data will be collected and made available to further test and evaluate the TPN methodology.

CHAPTER SEVEN

CONCLUSION

In remote sensing, texture is considered one of the seven photointerpretive elements employed to assist analysts in form recognition and image classification. With the advent of computer vision technology and the availability of remotely sensed multispectral satellite and airborne data, techniques have been designed with the intention of automatically extracting photointerpretive elements from digital imagery. Unfortunately many of these have met with limited success. In digital classification techniques, tonal variation or colour, is the primary property used to segment images. Texture is also an important attribute of digital images that is receiving more attention, as it is capable of describing a spatial aspect of the data as opposed to purely spectral characteristics.

In digital remote sensing, texture analysis typically involves quantifying the spatial variation of tones or intensities in a 2-D image. In human texture analysis, texture involves quantifying the physical size, shape, and spatial arrangement of the components that constitute a 3-dimensional scene, so that regions with similar structural characteristics may be delineated. Although the technology and theory is sophisticated, the current RS approach to classification still relies on a variety of supervised enhancement techniques to facilitate visual interpretation; yet many of these modern theories do not accurately emulate what the visual system does. A literature search indicates that traditional RS texture methodology is premised on dated second-order statistical vision texture theories, resulting in four main areas of discrepancy between human texture perception and RS texture analysis. These involve:

1. Defining appropriate primitives.
2. Quantifying the spatial arrangement of primitives.
3. Determining appropriate scale / spatial resolution.
4. The inclusion of depth information.

By adhering to current psychophysical haptic and vision texture theory, a structural texture methodology referred to as the triangulated primitive neighborhood method (TPN), has been designed that emulates the human visual system by employing object specific height

and area data, location specific primitives, and a variable sized and shaped moving window, to effectively discriminate the within- and between-stand textures of 2 different age class forest stands.

The textured vegetation surface under analysis is a 0.72 ha heterogeneous forest canopy, comprised of 208 trees located within the Sooke Watershed on Southern Vancouver Island. Structural canopy measurements such as the height, radii, and the geographic location of each tree have been obtained during ground truthing campaigns to 0.1 m precision, and modeled as a 2.5-D digital elevation model, referred to as a digital canopy model (DCM).

By incorporating height information within the TPN method, a hierarchy of object specific primitives have been created, that selectively reduced the spatial variation of DCM image primitives. This allowed a simple unsupervised per-pixel classifier (*k*-means) to be used on the H-resolution data set, to produce a visually correlative texture classification of the within-stand texture of 2 different age class forest stands, and of the fuzzy texture boundary between each stand based on spatial data only. Theory is also discussed suggesting methods to obtain height and object specific information from H-resolution RS spectral imagery.

Results indicate that both singly and in combination, Neighborhood Height and Area data applied to spatial specific object primitives are strong structural discriminators of H-resolution forest texture. Natural groupings of the same data sets also indicate a strong correlation between tree size (height per visible crown unit), and crown density (or spatial arrangement of 3 trees per TP area).

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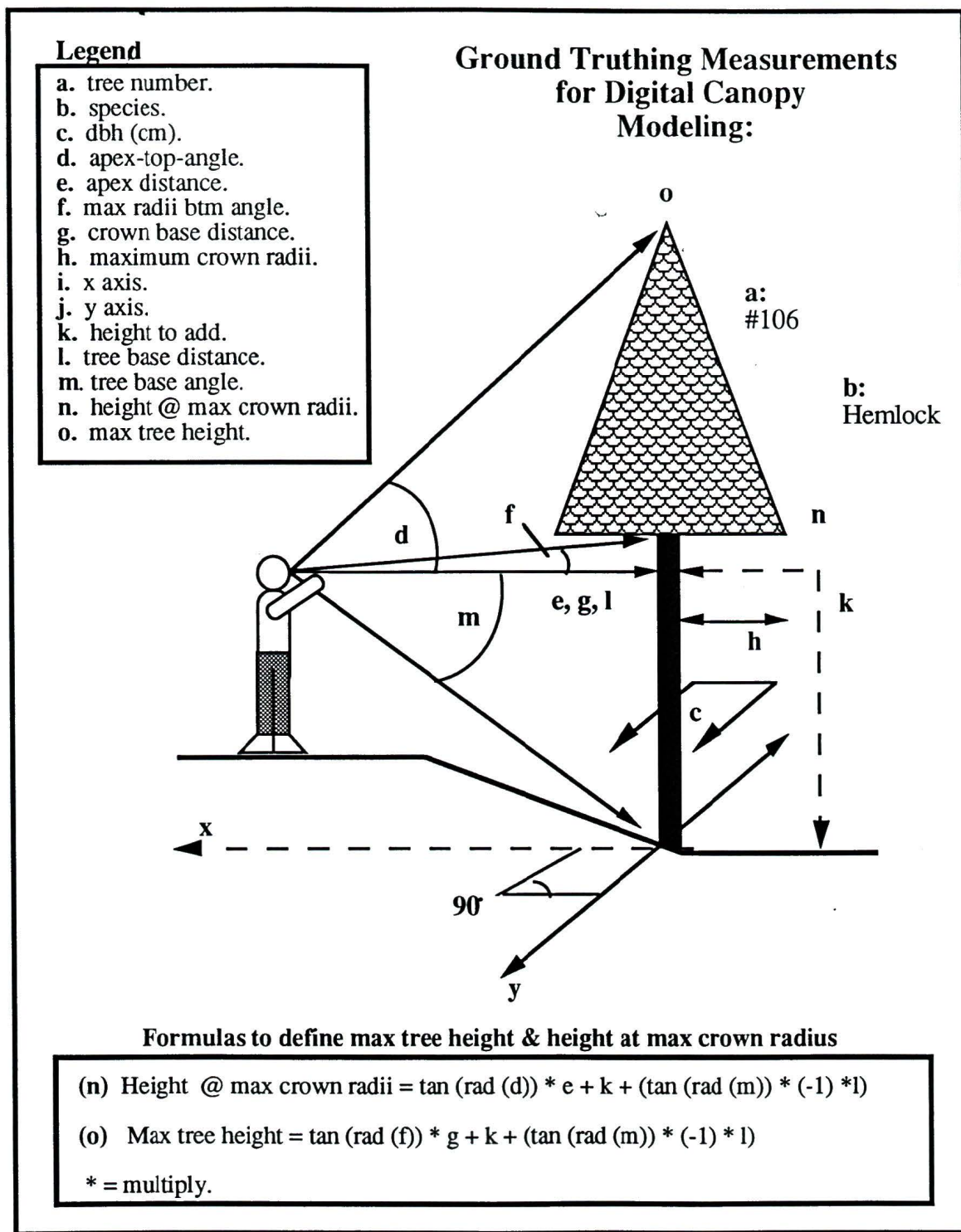
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APPENDIX 1.



NB: All numerical values are in meters unless otherwise stated.

An example of the structural canopy data obtained (from ground truthing) to construct the DCM. Headings (a) - (o) are explained in the legend on the previous page.

(a)	(b)	(c)	(h)	(i)	(j)	(n)	(o)
1	h	13	1.3	1.4	6.7	7.342322	11.15355
2	h	18	1.4	2.8	4	7.187659	18.84730
3	f	15	1	1	2.9	12.39222	15.84953
4	h	15	1	5.1	5.1	11.12511	13.19569
5	f	33	1.8	6.6	8.6	17.5	21.63418
6	h	22	1.5	9.9	2.5	10.37936	17.92340
7	f	16	1.1	11	7.8	9.252654	15.97774
8	f	9	0.7	12.9	0.1	6.933322	8.588937
9	f	17	1.1	14.3	7.9	11.25091	16.17783
10	f	13	0.7	14.1	3.9	9.263798	14.73607
11	f	19	1.6	16.8	1.8	9.830095	18.24247
12	f	24	1.7	19.6	2	13.47238	18.75026
13	f	20	1.2	19.7	7.9	11.30829	18.96592
14	f	24	1.3	22.2	8.2	12.00367	18.49421
15	f	28	1.8	23.4	1.7	14.48573	20.54403
16	f	21	1.6	25.8	3.6	10.71800	17.65724
17	f	27	1.5	26.5	7	13.31867	19.84313
18	f	12	1.2	28.5	3	8.054293	12.52518
19	h	16	1.3	29.3	6.6	10.71440	15.90256
20	f	20	1.5	31	11.6	9.615160	18.50047
21	f	21	1.5	31.3	19.2	14.19737	19.28375
22	h	83	3.5	37.8	15.7	26.01287	38.40370
23	f	22	1.5	31	22.3	9.797840	15.46381
24	f	24	2	31.2	28.5	10.72663	19.30850
25	f	24	1.8	30.5	31.7	10.97061	19.75497
26	f	23	2	30.8	35.5	10.19286	18.82050
27	f	17	1.7	30.2	40.6	9.187767	17.51461
28	h	14	1.2	33.8	66.4	8.403636	15.27851
29	h	63	2.4	39.5	61.4	15.95694	28.12191
30	h	27	1.6	30.5	74.8	11.47496	16.72265
31	f	16	1.2	32.2	76.5	10.89488	16.05724
32	f	19	1.3	34.5	78.1	12.6	17.53060
33	h	13	1.2	35.5	74.2	6.091805	9.329607
34	h	22	1.6	33.4	71.4	13.38881	16.70256
35	f	11	1	2.4	18.5	11.71105	14.55640
36	h	15	1.1	4.5	15.4	9.354905	13.06000
37	f	25	1.7	5	17.9	13.9	20.91824
38	f	21	1.4	7.7	14.7	14.42434	21.52695
39	f	20	1.5	9.9	19.9	12.86541	17.34762
40	f	20	1.3	9.1	13.2	13	16.35929
41	f	19	1.2	11.6	12.3	11.04451	15.93130
42	f	18	1.2	11.9	14.6	11.99692	18.54247
43	f	24	1.5	14.2	14.3	13.89947	18.80298

APPENDIX 2.

This section contains the C-programs *Testsurf*, *PIP*, and *Neighbors2*.

```
#include <math.h>
#include <stdio.h>
```

```
/*
TESTSURF.C is used to create two octagonal shapes. The first, around the crown apex
location of each tree, based on the tree radii at the maximum canopy extent; where the
height at this location is assigned to each of the eight (octagonal) points. The crown apex
height is assigned to the point at the center of the octagon. The second octagon is located
outside the first octagon at a distance of approximately 8.5% of the radii of each tree. The
height value assigned to the eight points of this octagon is 0, thus tying it into the ground of
the DCM. The value of  $\approx 8.5\%$  was due to modeling limitations in the DEM package used.
*/
```

```
/*
TO RUN THIS PROGRAM IN C TYPE: cc -lm filename.c
*/
```

```
main()
{
FILE *testsurf;          /* point locations (x,y,z) of tops & btms. */
FILE *input;             /* input file = radi, xtop, ytop, zbtm, ztop*/

float  xtop, ytop, ztop;
float  xbtm, ybtm, zbtm;
float  radi, PI;
float  newx, newy;

int    i, c;
PI     = 3.1416;
c      = 0.0;

testsurf = fopen("Geofftestsurf2", "w");
input    = fopen("input3", "r");

while(fscanf(input, "%f%f%f%f%f", &radi, &xtop, &ytop, &zbtm, &ztop) != EOF)
{
    fprintf(testsurf, "%f %f %f\n", (10*(xtop+3.0)), (10*(ytop+3.0)), (10* ztop));

    for(i = 1; i <= 8; i++)          /*    First octagon    */
    {
        xbtm = xtop + (0.7 * radi) * cos(2.0*PI/8.0 * (float)i + PI/8);
        ybtm = ytop + (0.7 * radi) * sin(2.0*PI/8.0 * (float)i + PI/8);

        fprintf(testsurf, "%f %f %f\n", (10*(xbtm+3.0)), (10*(ybtm+3.0)),
```



```

        (10* zbtm));
    }

    for(i = 1; i <= 8; i++)          /*    Second octagon    */

    {
        newx = xtop + (0.81 * radi) * cos(2.0*PI/8.0 * (float)i + PI/8);
        newy = ytop + (0.81 * radi) * sin(2.0*PI/8.0 * (float)i + PI/8);

        fprintf(testsurf, "%f %f %d\n", (10*(newx + 3.0)), (10*(newy + 3.0)), (c));
    }
}

```

```

#include <stdio.h>
#include <math.h>

```

```

/*    PIP_NODTM.C is a point-in-polygon routine that creates a variety of
height, area, and polygonal output based on two files: A DEM file of the
study site (structure_in), and a Delaunay triangles file (tringles - constructed
from the crown-apex location of all the trees within the study site).
*/

```

```

main ()
{
FILE  *tringles, *structure_in, *triangles_out;
int    i, j, k, l, t, ncols, nrows, izer0;
float  tag1, tag2, tag3, x, y, z, x0,y0,x1,y1,x2, y2, z2, x3, y3, z3;
float  pixelval;

```

```

struct  trinfo  {
        int      tri_id;
        int      xvert[3];
        int      yvert[3];
        int      trearea;
        int      non_trearea;
        int      ttl_triarea;
        float     ttlhgt;
        float     ttlhgt_by_trearea;    /* = tresize. */
        float     tresize_by_ttl_triarea;
        /* float   tresize_by_non_trearea;    */
    }            triangles[500];

```

```

tringles      = fopen("tringles3","r");
structure_in   = fopen("structure3.grd","r");
triangles_out  = fopen("triout4_shape_nodtm","w");

```

```

i=0;
while(fscanf(tringles,"%f %f %f %f", &tag1, &y, &x, &z) !=EOF)

```

```

{
fscanf(tringles,"%f %f %f %f", &tag2, &y2, &x2, &z2);
fscanf(tringles,"%f %f %f %f", &tag3, &y3, &x3, &z3);
    triangles[i].tri_id = tag1;
    triangles[i].xvert[0] = x;      /* The first space value in an */
    triangles[i].yvert[0] = y;      /* array is 0 not 1.          */
    triangles[i].xvert[1] = x2;
    triangles[i].yvert[1] = y2;
    triangles[i].xvert[2] = x3;
    triangles[i].yvert[2] = y3;
    i++;
}

while(fscanf(structure_in,"%f %f %f", &x, &y,&pixelval)!=EOF)
{

x+=0.5;          /* add 0.5 to each 1 value raster ensuring the */
y+=0.5;          /* center of the raster is measured in/or out. */

for(l = 0; l < i;l++)

/*
"l" goes through the list of triangles until reaching the end.
If a point (x,y) is outside a tri, the search goes to the next
tri, until it is found inside a tri.
*/
    {
        x0 = triangles[l].xvert[0];
        y0 = triangles[l].yvert[0];
        x1 = triangles[l].xvert[1];
        y1 = triangles[l].yvert[1];
        x2 = triangles[l].xvert[2];
        y2 = triangles[l].yvert[2];
        if (outside(x0,y0,x1,y1,x2,y2, x, y) == 1.0)
            {
                if(pixelval > 0.0)          /*
                                                This calculates tree height,
                                                tree area, and triangle area.
                                                */
                    {
                        triangles[l].trearea++;
                        triangles[l].ttlhgt+=pixelval;
                    }
                if(pixelval < 0.01)
                    {
                        triangles[l].non_trearea++;
                    }
                triangles[l].ttl_triarea = (triangles[l].trearea +
                triangles[l].non_trearea);
                break;
            }
    }
}

```



```

    }
    for(t = 0; t < i; t++)
    {
        triangles[t].ttlhgt_by_trearea=triangles[t].ttlhgt/triangles[t].trearea;
        triangles[t].tresize_by_ttl_triarea = triangles[t].ttlhgt_by_trearea/
                                           triangles[t].ttl_triarea;
        /*      triangles[t].tresize_by_non_trearea = triangles[t].ttlhgt_by_trearea/
                                           triangles[t].non_trearea;
        */

        fprintf(triangles_out, "%d %d %d %d %d %d %d %d %d %d %d %f %f %f %f\n",

                triangles[t].tri_id,triangles[t].xvert[0],triangles[t].yvert[0],
                triangles[t].xvert[1],triangles[t].yvert[1],triangles[t].xvert[2],
                triangles[t].yvert[2],triangles[t].trearea,triangles[t].non_trearea,
                triangles[t].ttl_triarea,triangles[t].ttlhgt,
                triangles[t].ttlhgt_by_trearea,triangles[t].tresize_by_ttl_triarea);
        /*      triangles[t].tresize_by_non_trearea */
    }
}
/*

```

'OUTSIDE' and 'SAME' are C translations of 'Fortran programs to construct the planar voroni diagram' by John C. Tipper. Computers and Geoscience Vol. 17, No. 5, pp. 597-632, 1991.

OUTSIDE checks to see if the point lies within the triangle.

```

/*
int  outside(x0,y0,x1,y1,x2,y2,cx,cy)
float x0,y0,x1,y1,x2,y2,cx,cy;

{
    float  xmean,ymean;
    int    i;

    xmean = 0.0;
    ymean = 0.0;

    xmean = (x0+x1+x2)/3.0;
    ymean = (y0+y1+y2)/3.0;

    if (same(xmean,ymean,x0,y0,x1,y1,cx,cy) == 0) return(0);
    if (same(xmean,ymean,x1,y1,x2,y2,cx,cy) == 0) return(0);
    if (same(xmean,ymean,x0,y0,x2,y2,cx,cy) == 0) return(0);

    return(1);      /* 1 = point has been found inside the triangle or on the line */
}                  /* 0 = point found outside the triangle.*/

/*

```

SAME checks to see if the point lies on the same side of the line as the central point(xmean,ymean) of the triangle.

```

*/

int  same(xmean,ymean,x1,y1,x2,y2,px,py)
float xmean,ymean,x1,y1,x2,y2,px,py;

{
float  xdif,ydif,a,b;

xdif = x2 - x1;
ydif = y2 - y1;
a = (ymean - y1) * xdif - (xmean - x1) * ydif;
b = (py - y1) * xdif - (px - x1) * ydif;

if(fabs(a) < 0.000001) a = 0.0;
if(fabs(b) < 0.000001) b = 0.0;
if(a * b < 0.0) return(0);
    else return(1);
}

```

```

/*
NEIGHBORS2_NODTM.C - finds the value of each triangle surrounding a
central triangle, and averages the surrounding (height_by_area) triangle values
generated in the (PIP.C) 'triout' file, to the center triangle. Essentially, this is the
final portion of a variable shaped and sized moving window extraction technique.

```

```

*/

#include <stdio.h>
#include <math.h>

main ()
{
FILE  *structure_in, *tringles, *triout, *check1, *check2;
FILE  *check3, *check4, *output1, *output2;
int    i, j, k, l, q, t, ncols, nrows, num_triangles, count;
float  areaval, pixelval, sizeval, ttlhgt, hgt_by_trearea, trearea, triarea;
float  tag1, tag2, tag3, x, y, z, x0, y0, x1, y1, x2, y2, z2, x3, y3, z3;
float  non_trearea, tresize_by_triarea, blank;

struct  trinfo  {
        int      tri_id;
        int      xvert[3];
        int      yvert[3];
        int      trearea;
        float     ttlhgt;
        float     ttlhgt_by_trearea;    /* = tresize      */
        float     tresize_by_ttl_triarea;
        float     ttl_triarea;
        float     sizeavg;

```



```

        float   areavg;
    }          triangles[500];

structure_in = fopen("structure3.grd","r");
triout       = fopen("triout4_shape_nodtm","r");
output1      = fopen("testhood_sizeavg4_nodtm","w");
output2      = fopen("testhood_areavg4_nodtm","w");
check1       = fopen("testcheck_sizeavg4_nodtm","w");
check2       = fopen("testcheck_stats_sizeavg4_nodtm","w");
check3       = fopen("testcheck_areavg4_nodtm","w");
check4       = fopen("testcheck_stats_areavg4_nodtm","w");

num_triangles = 0;
while(fscanf(triout,"%f %f %f %f %f %f %f %f %f %f %f %f %f",
&tag1,&x0,&y0,&x1,&y1,&x2,&y2,&trearea,&non_trearea,&triarea,
&tthgt, &hgt_by_trearea, &tresize_by_triarea,&blank) !=EOF)
{
    triangles[num_triangles].tri_id = tag1;
    triangles[num_triangles].xvert[0] = x0;      /* the first space value in an */
    triangles[num_triangles].yvert[0] = y0;      /* array is 0 not 1.          */
    triangles[num_triangles].xvert[1] = x1;
    triangles[num_triangles].yvert[1] = y1;
    triangles[num_triangles].xvert[2] = x2;
    triangles[num_triangles].yvert[2] = y2;
    triangles[num_triangles].tthgt_by_trearea = hgt_by_trearea;
    triangles[num_triangles].tresize_by_ttl_triarea = tresize_by_triarea;
    triangles[num_triangles].ttl_triarea = triarea;
    num_triangles++;
}

for(i=0; i<num_triangles; i++)
{
    count          = 1.0; /* this counts the center tri as the first tri. */
    sizeval        = triangles[i].tthgt_by_trearea;
    areaval        = triangles[i].ttl_triarea;

    for(q=0; q<num_triangles; q++)
    {
        if(i != q)
        {
/*
    Proof to determine if the vertices (x,y) of one triangle[i] shares
    at least one of the 3 vertices of triangle[q]. If not, the next
    triangle is examined. If so, a new tthgt_by_trearea value is
    calculated, and count is incremented by 1. Each triangle is
    examined against all other triangles.
*/

            if((triangles[i].xvert[0] == triangles[q].xvert[0] &&
                triangles[i].yvert[0] == triangles[q].yvert[0]) ||

```

```

        (triangles[i].xvert[0] == triangles[q].xvert[1] &&
         triangles[i].yvert[0] == triangles[q].yvert[1]) ||
        (triangles[i].xvert[0] == triangles[q].xvert[2] &&
         triangles[i].yvert[0] == triangles[q].yvert[2]))
        {
            sizeval+= triangles[q].ttlhgt_by_trearea;
            areaval+= triangles[q].ttl_triarea;
            count++;
        }
    else if((triangles[i].xvert[1] == triangles[q].xvert[0] &&
             triangles[i].yvert[1] == triangles[q].yvert[0]) ||
            (triangles[i].xvert[1] == triangles[q].xvert[1] &&
             triangles[i].yvert[1] == triangles[q].yvert[1]) ||
            (triangles[i].xvert[1] == triangles[q].xvert[2] &&
             triangles[i].yvert[1] == triangles[q].yvert[2]))
        {
            sizeval+= triangles[q].ttlhgt_by_trearea;
            areaval+= triangles[q].ttl_triarea;
            count++;
        }
    else if((triangles[i].xvert[2] == triangles[q].xvert[0] &&
             triangles[i].yvert[2] == triangles[q].yvert[0]) ||
            (triangles[i].xvert[2] == triangles[q].xvert[1] &&
             triangles[i].yvert[2] == triangles[q].yvert[1]) ||
            (triangles[i].xvert[2] == triangles[q].xvert[2] &&
             triangles[i].yvert[2] == triangles[q].yvert[2]))
        {
            sizeval+= triangles[q].ttlhgt_by_trearea;
            areaval+= triangles[q].ttl_triarea;
            count++;
        }
    }
}
triangles[i].sizeavg = (sizeval/count)/10;
triangles[i].areavg = (areaval/count)/100;
/*
'Check1 & 3' provide data (452 tri-values) for integration into histograms
to check for natural breaks. 'Check2 & 4' provide a way to determine if the
program is comparing a central triangle with its neighbors, and maintains
a record of how many neighbours and their total (averaged) values.
*/
fprintf(check1,"%f\n",triangles[i].sizeavg);
fprintf(check2," %d %f %f %d\n\n", i, triangles[i].sizeavg, sizeval, count);
fprintf(check3,"%f\n",triangles[i].areavg);
fprintf(check4," %d %f %f %d\n", i, triangles[i].areavg, areaval, count);
}
while(fscanf(structure_in,"%f %f %f", &x, &y,&pixelval)!=EOF)
{
    x+=0.5;
    y+=0.5;
    for(l = 0; l < num_triangles;l++)

```



```

/* "l" goes through the list of triangles until reaching the end.*/

    {
        x0 = triangles[l].xvert[0];
        y0 = triangles[l].yvert[0];
        x1 = triangles[l].xvert[1];
        y1 = triangles[l].yvert[1];
        x2 = triangles[l].xvert[2];
        y2 = triangles[l].yvert[2];
        if (outside(x0,y0,x1,y1,x2,y2, x, y) ==1)
        {
/* if (x,y) is outside tri, goto next tri, until inside tri. */

            fprintf(output1,"%d %d %7.2f\n",(int)x,(int)y,
                triangles[l].sizeavg);
            fprintf(output2,"%d %d %f\n",(int)x,(int)y,
                triangles[l].areavg);
            break;
        }
    }
}

/*
'OUTSIDE' and 'SAME' are C translations of 'Fortran programs to construct
the planar voroni diagram' by John C. Tipper. Computers and Geoscience
Vol. 17, No. 5, pp. 597-632, 1991.

OUTSIDE checks to see if the point lies within the triangle.

*/

int    outside(x0,y0,x1,y1,x2,y2,cx,cy)
float  x0,y0,x1,y1,x2,y2,cx,cy;

    {
float  xmean,ymean;
int    i;

xmean = 0.0;
ymean = 0.0;
        xmean = (x0+x1+x2)/3.0;
        ymean = (y0+y1+y2)/3.0;

        if (same(xmean,ymean,x0,y0,x1,y1,cx,cy) == 0) return(0);
        if (same(xmean,ymean,x1,y1,x2,y2,cx,cy) == 0) return(0);
        if (same(xmean,ymean,x0,y0,x2,y2,cx,cy) == 0) return(0);

return(1);    /* 1 = point has been found inside the triangle or on the line */
    }          /* 0 = point found outside the triangle.*/

```

```

/*
    SAME checks to see if the point lies on the same side of the line
    as the central point(xmean,ymean) of the triangle.
*/

int  same(xmean,ymean,x1,y1,x2,y2,px,py)
float xmean,ymean,x1,y1,x2,y2,px,py;

{
    float  xdif,ydif,a,b;

    xdif = x2 - x1;
    ydif = y2 - y1;
    a = (ymean - y1) * xdif - (xmean - x1) * ydif;
    b = (py - y1) * xdif - (px - x1) * ydif;

    if(fabs(a) < 0.000001) a = 0.0;
    if(fabs(b) < 0.000001) b = 0.0;
    if(a * b < 0.0) return(0);
        else return(1);
}

```


APPENDIX 3.

List of Abbreviations.

Defined at:

ASM	-	Angular Second Moment.	pp.24
CASI	-	Compact Airborne Spectrographic Imager.	pp.6
CV	-	Computer Vision.	pp.7
DCM	-	Digital Canopy Model.	pp.33
DEM	-	Digital Elevation Model.	pp.20
DN's	-	Digital numbers.	pp.22
GIS	-	Geographic Information System.	pp.18
GLCM's	-	Grey level cooccurrence matrix methods	pp.22
H-res	-	High resolution.	pp.5
L-res	-	Low resolution.	pp.5
MEIS	-	Multispectral Electro-optical Imaging Sensor.	pp.6
MSS	-	Multispectral scanner system.	pp.5
OP's	-	Object Primitives.	pp.48
PIP	-	Point in Polygon.	pp.72
RS	-	Remote sensing	pp.2
TM	-	(Landsat) Thematic mapper.	pp.5
TP's	-	Texture Primitives.	pp.48
TPN	-	Triangulated Primitive Neighborhood (method).	pp.42

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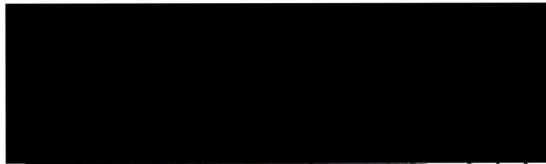
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APPROACH TO MODEL FOREST TEXTURE.

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9 Sept '93

(Date)