2 Pattern Progressions and Segmentation Sequences for IMAGE Intensity Modeling and Grouped Enhancement

The foregoing background regarding multiband digital image data provides a basis for pursuing our primary focus on patterns in landscape images. Landscapes are characterized by spatial autocorrelation (Schabenberger & Gotway, 2005) whereby things closer together tend to appear more alike than things that are further apart with some changes being gradational and others abrupt, which induces implicit perception of pattern. However, the indefiniteness of implicit pattern perception limits its utility. In landscape ecology, pattern has been most often addressed in terms of variously defined mosaics and parameters of patchiness (Forman & Godron, 1986; Forman, 1995; McGarigal & Marks, 1995; Turner, Gardner & O'Neill, 2001). Furthermore, pattern is a much used but rather varied conceptual construct for image analysis, as witness the lineage of literature relating to 'pattern recognition' including a journal so named along with disparate sources (Tou & Gonzales, 1974; Pavlidis, 1977; Gonzales & Thomason, 1978; Fu, 1982; Simon, 1986; Pao, 1989; Jain, Duin & Mao, 2000; Duda, Hart & Stork, 2001; Webb, 2002) and extensions into the contemporary topics of clustering, classification, machine learning, data mining and knowledge discovery. Therefore, an obvious next task is to resolve some of the indefiniteness regarding pattern in the current context. As a point of departure, we take the succinct statement of Luger (2002) that pattern recognition is identifying structure in data.

2.1 Pattern Process, Progression, Prominence and Potentials

We designate L as the set of pixel positions comprising the image lattice. Let us further reference the pixel position at row *i* and column *j* as being L(*i,j*). We likewise designate V as the entire set of different signal vectors. Each of these vectors can be considered as a point in the space of signal properties, which we will call signal domain. Let us further reference a particular one of these *property points* as being pp_k for the kth such point in some fixed order. It should be intuitively apparent that a notion of landscape pattern must be a joint construct in the spatial domain L and the signal domain V. Accordingly, we define a *pixel pattern* or *pattern of pixels* PP_k as being the subset of pixels sharing the same property point pp_k (signal vector) and indexed by the index of the property point. We proceed to consider a process that assigns property points to pixels forming an initial image as being a *pixel process* symbolized by a superscript # resulting in a set $PP^{\#}$ of *primitive patterns*. Image data for landscapes tend to have large numbers of primitive patterns each of which encompasses relatively few pixels with considerable fragmentation and interspersion. Part of this multiplicity arises from 'edge effects' where pixels span boundaries in the landscape. Thus the primitive patterns tend to be visually subtle or weak. Our intent is to strengthen these patterns so that they become less numerous but more apparent and better segregated.

Toward this end, we now define a *pattern process* as one that produces sets or subsets from *prior patterns* to yield either more general or more specific *posterior patterns*. All of the pixels in a particular posterior pattern will share the same property point, which serves as *proxy* for whatever property point was applicable in a prior pattern. If a pattern process operates recursively, we call it a *progressive pattern process* and refer to its recursive sequence of pattern sets as a *pattern progression*. Since it operates across the image lattice L, we use the symbol £ to denote a pattern process.

An important aspect of pattern processes is the strength of the patterns that they produce. In order to make these concepts operational, however, measures of strength for patterns are needed. As a simple expression of pattern strength, we define *prominence of a pattern* to be the proportion p_k of non-null pixels for the kth pattern in the lattice. This is one formulation of what we will call a *mass function* M(k) for the kth pattern.

Continuing with measures of strength for patterns, we emulate physics with analogies to ideas of potentials in fields of charged particles. Let the *potential of a pattern* or simply *pattern potential*, symbolized as Pp, have the form of Eq. 2.1

$$\mathrm{Pp}(k) = [1 + a_1\mathrm{M}(k) + a_2\mathrm{M}(n_k)]\ \mathrm{D}^z_{\mathrm{w}}(k,n_k) \tag{2.1}$$

where

M(k) is a mass function for the kth pattern;

D_w is a (weighted) distance function between property points in signal space;

a_1 and a_2 are 'aggregation' parameters;

z is a 'zonal' parameter;

n_k is the nearest neighbor of property point pp_k by D_w in the signal domain.

Note that Pp(k) pertains to a definite pattern PP_k relating a particular property point pp_k to a particular set of pixel positions. In parallel manner and with some appeal to the dual ideas of definite and indefinite integrals, we define a *potential pattern* pP(k) pertaining to a property point that is decoupled from any particular positions using the same formula as for Pp(k) but with a mass function that does not explicitly reference positions in the lattice. *Intrinsic potential* pP'(k) is obtained by setting the aggregation parameters to zero, which inherently decouples property points from pixel positions since the distance is measured in the signal domain.

The aggregation parameters and mass functions have an effect of local dilation or expansion of signal space. Two patterns effectively have greater separation with increase of any parameter. Even when the aggregation parameters are equal, a pattern does not necessarily have the same potential as its nearest neighbor because that neighbor may have a different nearest neighbor.

2.2 Polypatterns

In order to strengthen subtle patterns without suppressing them completely, we can work with patterns of patterns as compound patterns or *polypatterns*. This entails multi-level indexing of patterns to form nested patterns. Thus, we can have a first (strong) level of numbered patterns along with a table of property vectors (points) for those strong patterns. Then each of the first-level patterns can be disaggregated into a numbered series of second level patterns, each having another more specific property vector that differentiates it from others having like index and vector at the first level. We designate the aggregated level of a bi-level pattern as the A-level, and the disaggregated level as the B-level (base level). Property vectors in the A-level serve as *proxies* for property vectors in the B-level. To minimize further complexity of notation, polypatterns can be symbolized by prefacing an entire pattern reference with the ‡ (double dagger) symbol in the notation previously defined where clarification is required. Thus, ‡p_k symbolizes the prominence of the kth polypattern.

In constructing index numbers as identifiers for polypatterns, the second level of numbering can either run across the first levels globally or be conditional within the first level. The global approach is more convenient for accessing look-up tables of the more detailed (B-level) pattern properties, but the larger sizes of the index values involved also occupies more computer media and thus reduces the degree of compression.

As a compromise, we use conditional numbering but also record the cumulative number of finer segments by pattern number in the coarser level. Let m_k be the number of disaggregated patterns in the kth polypattern, and let these patterns be conditionally numbered $1 \ldots m_k$. As a globally sequential index $g_{k,i}$ to the ith disaggregated (B-level) pattern in the kth polypattern we use Eq. 2.2.

$$g_{k,i} = i + \sum m_{j<k} \tag{2.2}$$

This index can be computed dynamically from the A-level polypattern numbers and the conditionally (nested) numbers of the disaggregated patterns coupled with a distributional list of pattern frequencies for the A-level polypatterns. The only overhead of computer media relative to compression is for storing the distributional list of pattern frequencies for A-level polypatterns.

The creation of polypatterns allows for exploitation of the ideas underlying 'constrictive analysis' as described by Myers, Patil and Taillie (2001). Polypatterns should also help to clarify our 'proxy' terminology for property vectors associated with pattern processes. A property vector at the aggregated A-level serves as a proxy for all of the patterns encompassed at the disaggregated B-level.

2.3 Pattern Pictures, Ordered Overtones and Mosaic Models of Images

A set of PP patterns forms a spatial mosaic on the image lattice, regardless of whether these are primitive patterns, clustered (proxy) patterns, or polypatterns. To the degree that the signal values in the pp property points of the patterns may be reasonable proxies for the original pixel vectors, it should be possible to treat a mosaic of patterns as an approximate model of the image data from which they were obtained. Likewise, a *pattern picture* resembling the original image should be obtainable by using selected elements of the pattern properties to portray the patterns as tones in a mapping mode.

Such graphic image emulation is facilitated by making it possible to treat an A-level pattern mosaic like a simple single band of image data for direct display.

An image-like mosaic can be constructed by making the pattern index numbers correspond with the ordering of overall intensity using the signal bands comprising the pattern vectors (property points). The patterns having lesser overall intensity for their signal bands are given lower index numbers, and those having greater overall intensity are given higher index numbers. In other words, the patterns are ranked according to overall (or average) intensity and the rank number becomes the identifying index number for the pattern. The pattern index numbers are entered directly in an image lattice. The pattern numbers thus become an index image of overall signal intensity which can be treated as brightness in a gray-tone image. The norm (or length) of the signal vector as distance of the property point from the origin of signal space is one convenient measure of overall intensity, computed as the square root of the sum of squared signal values and being a multiple of the quadratic mean of the values across signal bands. *Ordered overtones* appear in a pattern picture that translates the pattern identification numbers directly to gray tones.

Ordered overtones derived from ASTER sensor data for central Pennsylvania are shown in Fig. 2.1 as produced by pattern processes described subsequently. The ASTER acronym is for Advanced Spaceborne Thermal Emission and Reflection Radiometer on a Terra satellite operated by NASA with Japanese cooperation. The image data used as a basis for Fig. 2.1 were acquired by the sensors on September 6, 2002. Ten ASTER bands were harmonized in 15-meter pixels, with the central wavelengths of the spectral bands being as shown in Table 2.1.

Table 2.1 Center wavelength (μm) of ASTER bands used for Fig. 2.1.

Band Number	Center wavelength (μm)
1	0.556
2	0.661
3	0.807
4	1.656
5	2.167
6	8.291
7	8.634
8	9.075
9	10.657
10	11.318

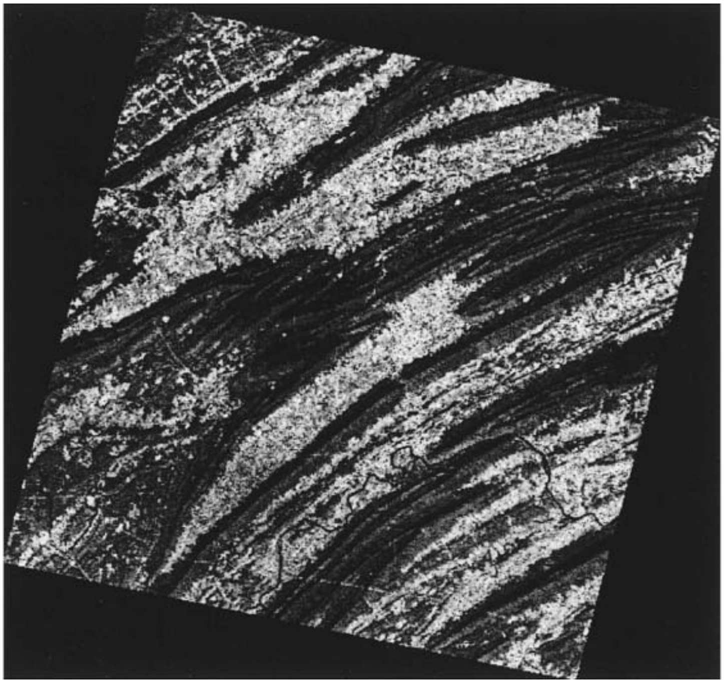

Fig. 2.1 Ordered overtones of ASTER satellite data for central Pennsylvania, September 2002.

Similarly, Fig. 2.2 shows ordered overtones of the six-band vertebrate species richness data for Pennsylvania developed in like manner. Since signal intensity corresponds to increasing species richness, the lighter (brighter) areas in Fig. 2.2 exhibit greater species (habitat) richness as averaged over the taxonomic groups being treated in the manner of signal bands as described in Chap. 1.

Despite this quasi-quantitative treatment of identifying indexes for polypatterns, we should not lose sight of the fact that our patterns are inherently categorical constructs. The properties of a pattern are quantitative, but a pattern is a categorical collective.

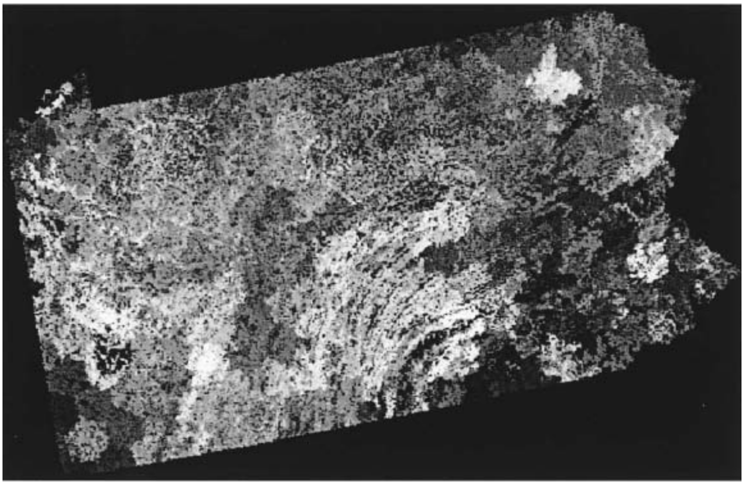

Fig. 2.2 Ordered overtones of habitat richness patterns in Pennsylvania for six groups of vertebrate species being treated as signal bands with lighter as greater.

2.4 Pattern Processes for Image Compression by Mosaic Modeling

The foregoing background and definitions lay the groundwork for using segmentation sequences as progressive pattern processes for image compression by mosaic modeling for purposes of landscape analysis as explored in subsequent chapters. The overall goal is a parsing of patterns in which the proxy properties for the patterns closely approximate the pixel primitives of the image while being few enough to record using substantially less electronic media than occupied by the original image data. In a general sense, this is a problem of strategically segmenting the image. In a statistical sense, this falls most directly under the subject of cluster analysis. However, our approach involves configurations and combinations of processes that are not conventional with regard to either clustering or image analysis.

There are four important aspects of the undertaking. One is to strengthen the primary patterns in the image so that landscape structure becomes more evident. A second is to retain substantial information regarding subtle patterns in the image, particularly so as not to induce extensive areas that are lacking in any detail. A third is to achieve a substantial degree of compression within these constraints. Fourth is to accomplish all of these in a manner that is computationally practical for large images, with this latter being somewhat dependent on the computer configuration. Therefore, compromise is inherent – which favors heuristics over optimization.

The first and second aspects can be accommodated through bi-level polypatterns, in which the stronger primary patterns comprise an A-level and more subtle pattern variants comprise a B-level. Even with polypatterns, the fourfold problem is excessively open-ended; which can be remedied somewhat by adding a fifth aspect of having the primary patterns be compatible with geographic information systems (Burrough & McDonnell, 1997; Chrisman, 2002; DeMers, 2000). The desired compatibility can be achieved by allotting one byte per pixel as a GIS raster (cellular grid) layer. The layer structure for primary patterns is then complemented by allotting a second byte per pixel for the more subtle pattern components in the B-level of polypatterns. Since it is common practice to record image data with one byte per band in each pixel, this structure essentially occupies the equivalent of two bands of image data. The degree of compression afforded by the fixed layer structure of polypatterns will thus depend on the number of bands, being inapplicable for fewer than three bands. The fixed layer structure is also amenable to further content-based compression, provided that the requisite layer arrangement is restored by decompression prior to usage.

One byte affords a possible 256 pattern distinctions in the A-layer. However, zero is needed as a designator for pixels in the lattice that do not pertain to the image area of interest – thus leaving a possible 255 pattern distinctions. A strategic decision has been made to reserve five designators for special usage in GIS mapping, thus providing for 250 primary patterns in the A-layer. Each of the 250 A-level patterns can have 255 B-level sub-patterns, therefore allowing for a total of 250×255=63,750 patterns. The usual number of patterns will be at least an order of magnitude less than this due to computational constraints and unequal distribution of subtle variants among the 250 primary patterns.

There are two avenues of analysis toward this sort of polypattern parsimony, and both involve several stages of image segmentation and/or clustering. One is to segregate 250 segments in the early stages, and then segment the segments in later stages. The other is fine segmentation in the early stages, and then later stage aggregation of fine segments as primary patterns. Other avenues of alternation in segregations and aggregations are also possible. Our approaches entail four phases.

Since these are compound pattern process scenarios with patterns representing image segments, the idea of a *segmentation sequence* becomes useful. Aside from primitive pixel patterns, the number and type of patterns arising from a particular segmentation stage becomes important. Therefore, the notation of Eq. 2.3 for a segmentation sequence is used to symbolize a scenario $£_\alpha$ that entails four stages producing 250, 250, 2500 and 250 patterns, respectively, with the kinds of patterns as explained below.

$$£_\alpha\{\#250?|\#250*|\#2500*|*250‡\} \quad (2.3)$$

As defined previously, the symbol £ is generic for a pattern process. The subscript α indicates that this is the particular 'alpha' segmentation sequence of pattern processes. The numbers in curly brackets are the numbers of patterns produced by the respective stages. The vertical bar | symbol separates the stages comprising the sequence. The leading and trailing symbols for the numbers indicate the kind of pattern that the stage operates upon and the kind of pattern that it produces, respectively. The # symbol indicates a primitive pattern, the **?** symbol indicates a potential pattern, the * symbol indicates a proxy pattern, and the ‡ symbol indicates a polypattern. Thus the first stage of this sequence operates on primitive patterns and produces 250 potential patterns; the second stage operates on primitive patterns and produces 250 proxy patterns; the third operates on primitive patterns and produces 2500 proxy patterns; the fourth operates on proxy patterns and produces 250 polypatterns.

2.5 α-Scenario Starting Stages

Our initial analytical approach to pattern parsing is an α-scenario that has been extensively tested on images and provides the point of departure for subsequent scenarios. It consists of a four-stage segmentation sequence as addressed above.

This produces bi-level polypatterns that are mapped into two bytes for each pixel as two 1-byte lattices with auxiliary tables. The aggregated A-level of patterns is arranged as ordered overtones that can be rendered directly as a gray-scale image. The (finer) B-level of the polypatterns must be decompressed with custom software to obtain more generic data for input to other software packages having facilities for image analysis.

The first stage of the α-scenario takes primitive patterns from multiband image data in byte-binary BIP format and produces 250 potential patterns as output. This process is based on intrinsic potentials for property points using the square of (weighted) Euclidean distance (zonal parameter z=2) as Eq. 2.4.

$$pP'(k) = D^2_w(k, n_k) \tag{2.4}$$

The first 250 non-duplicate pixels in the data file are taken as the initial potential patterns, among which the weakest potential will be shared in a pair. Each subsequent pixel is considered with regard to intrinsic potential among the current set, displacing the first of the weakest pair if it is stronger. Since the signal vectors of the pixels are considered conditionally on their order of occurrence in the file, this does not necessarily yield the strongest set of potential patterns; however, it does give a strong set encompassing property points that are well distributed in signal space. Unequal weighting of the signal bands for computation of squared distance is optional, with the defaults being unit weights.

The second stage of the α-scenario scans the primitive patterns from the same multiband image data and produces pixel patterns (PP) by associating each pixel with the potential pattern to which it is closest by (weighted) Euclidian distance in signal space (i.e., closest property point). Thus the potential patterns from the first stage become the proxies for the pixel patterns from the second stage. These pixel patterns are then ranked according to norm of signal vector for overtone in concluding the second stage.

2.6 α-Scenario Splitting Stage

The third stage of the α-scenario partially disaggregates the (proxy) pixel patterns from the second stage, but works with primitive patterns from the original image in doing so. Disaggregating is accomplished by recursive (unequal) bifurcations, thus making a tree of (binary) branching nodes for those patterns that are subject to splitting. Not all of the pixel patterns from the second stage, however, are subject to splitting. Computational constraints also impose practical limits on the number of (nodal) bifurcations that can be conducted concurrently. Therefore, (tunable) parameters of practicality affect the course of the disaggregating process. The set of (primitive) patterns for a node of the tree constitutes a *constellation* of property points in signal space.

The fundamental mechanism of splitting in the α-scenario is one of polar proximity according to Euclidean distance. For each node, the signal vector having the largest norm (most intense or 'brightest') and smallest norm (least intense or 'darkest') are determined as poles of an axis spanning the constellation of property points. When bifurcation takes place, those primitive patterns closest to each of the two poles become pattern subsets; and the poles of the subsets are determined in doing the segregation. A synthetic signal vector is calculated as the middle of the polar axis by averaging the respective components of bright and dark poles to serve as proxy for the new nodal subset. In short, the proxy point is at the mid-range of intensities. Figure 2.3 is a diagrammatic representation of this splitting.

We extend the idea of potentials to obtain a prioritizing criterion Φ for splitting. This criterion, which we call *polar potential*, is computed for each node by Eq. 2.5 as the product of the inter-polar or axial (Euclidean) distance and the number of pixels comprising the node,

$$\Phi_{k,j} = (\Delta_{k,j})(\varphi_{k,j}) \tag{2.5}$$

where $\Delta_{k,j}$ is the axial or inter-polar distance for the jth node in the kth second-stage pattern, and $\varphi_{k,j}$ is the number of pixels in that nodal group (subset). The polar potential criterion thus reflects both prominence and diversity of the parent pattern.

Concurrent splitting is conducted for the H highest nodes as ordered on the polar potential criterion, where H is the computational capacity for concurrent splitting. A minimum threshold is also imposed on the criterion for a node to be eligible for splitting. The polar potentials are recomputed after each episode (cycle) of concurrent splitting, with new nodes being considered for the queue. Since the number of nodes can only increase by H in each cycle, there is effectively a competition for place in the splitting queue, with advantage going to prominence and diversity. The capacity H for concurrent splitting is one of the factors of the competition, with a higher capacity allowing smaller and less diverse nodes to be split. As a consequence, lower capacity for splitting gives greater depth in structure of the trees and requires more cycles to reach a given number of nodal patterns. An overall limit on number of nodes is also imposed so that the ultimate polypatterns can be coded in two bytes per pixel.

2.7 α-Scenario Shifting Stage

The fourth and final stage in the α-scenario is one of rearranging aggregations that operates on the nodal patterns of the third stage instead of upon primitive patterns of the original image data. This process (re)groups the nodal patterns of the previous stage into A-level polypatterns. Individual differences between primitive patterns in a nodal constellation are dis-

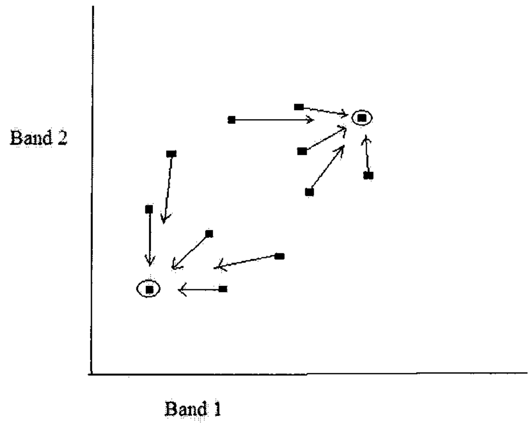

Fig. 2.3 Diagrammatic representation of polar partitioning. Small rectangles are property points for 2-band signal vectors. Enclosed property points are poles.

carded in formulating the final bi-level polypatterns. The primitive patterns of the original image can only be approximated with at least some error in at least some of the pixels. The polypatterns thus constitute a 'lossy' compression of the original image data (Gonzalez & Woods, 2002). The combination of pattern enhancement, compression, mapping and inherent inability for exact restoration makes the polypattern image intensity model a fundamentally different derivative product from the original image data in the same manner as a thematic map would be. Thus, copyright restrictions on redistribution of the original data should be obviated in most respects.

The fourth-stage (re)aggregation again entails compromise between competing practicalities. Overall information content for the A-level is favored by avoiding large discrepancies in prominence between the A-level patterns. This follows from information theory, but also from simply viewing each pattern as a carrier of information with a view to not having available carriers that are nearly empty. On the other hand, relatively restricted features of landscape pattern such as roads, streams and smaller water bodies tend to be defining features of terrain that should not be lost by blending with more ubiquitous pattern elements. By way of compromise, a target minimum prominence for aggregated patterns is a process parameter along with the obligatory maximum of 255 B-level members per A-level pattern for two-byte encoding. The target minimum prominence incorporated in the algorithm is p=0.00025, which is one-fortieth of one percent of the pixels.

The nodal trees for the second-stage A-level patterns provide an organizing template for the ultimate polypatterns. Preference is given to retaining such a tree as an A-level unit provided that it encompasses minimum prominence and does not exceed 255 nodes. If a tree does not attain minimum prominence, it is preferentially augmented by shifting nearest (by Euclidean distance) nodes from neighboring trees on a single-linkage (Podani, 2000; Mirkin, 2005) basis according to proxy signal vectors. Since the nodal splitting mechanism can segregate some very sparse patterns, a minimum prominence is also operative in this regard and similar single-linkage nodal shifts made accordingly. The final restructuring is to prune any remaining trees with more than 255 nodes backward from the terminals (by collapsing previous splits) to reach the 255 limit.

A segmentation sequence for the overall α-scenario takes the form of Eq. 2.6 with the actual number of third-stage patterns depending on the

$$£_\alpha\{\#250?|\#250^*|\#\max 63500^*|^*250‡\} \tag{2.6}$$

capacity for concurrent splitting and number of splitting cycles conducted. The algorithmic implementation allows splitting to be continued across several computing sessions.

The ordered overtone images in Figs. 2.1 and 2.2 were generated by this α-scenario. The segmentation sequence for Fig. 2.1 is:

$$£_\alpha\{\#250?|\#250^*|\#1898^*|^*250‡\} \tag{2.7}$$

and the segmentation sequence for Fig. 2.3 is:

$$£_\alpha\{\#250?|\#250^*|\#1248^*|^*250‡\} \tag{2.8}$$

Mirkin (2005) advocates capability for data recovery as a means of evaluating a method of clustering. Recovery of information along with mapping the spatial distribution of relative residuals for the α-scenario is considered later.

The α-scenario of polypattern processing is highly heuristic and was developed adaptively during the course of several years for different project purposes using a variety of image data sources, as well as being used extensively for instructional purposes in image analysis. The inception of that scenario was influenced by the early work of Kelly & White (1993). It has been consistently very robust in these various contexts. Recent work, however, has revealed several opportunities for enhancement, extension, and formalization that are elaborated here in terms of a -scenario.

2.8 β-Scenario Starting Stages

As an initial concern, the first stage of the α-scenario treats all primitive patterns equally whether they occur in only one pixel or thousands of pixels. The earlier formalization of pattern potentials is intended to address this aspect in a comprehensive manner while providing substantial scope for investigation. Using the generalized formulation of potential, this particular concern can be handled straightforwardly by changing the first stage of the segmentation sequence from the simple distance displacement process based on intrinsic potentials to a competitive assimilation process with the aggregation parameters for potentials set to a_1=1 and a_2=0.5 with a mass function in terms of partial prominence.

Therefore, let potential be specified as in Eq. 2.9,

$$pP_\beta(k) = [1 + M_\beta(k) + 0.5M_\beta(n_k)]\ D^2_w(k,n_k) \tag{2.9}$$

where
$M_\beta()$ = partial prominence as fraction of pixels in current partial image;
k = kth pattern;
n_k = nearest neighbor of k in signal space by using distance function D_w;
D_w = (optionally weighted) Euclidean distance.

Then a first-stage process for potential patterns (conditional on order of pixels in an image) operates as follows. Begin by obtaining the first 250 non-duplicate pixels from the file, using any duplication as frequency counts for mass functions. If there are no duplicates in this initial part of the image file, then the starting potentials are the same as for the α-scenario. For each subsequent pixel in the encountered order there is a competition that results in assimilation of a potential pattern by a neighbor pattern. The potential for each of the 250 current patterns is determined along with the potential of the next pixel as an additional pattern relative to the other 250. The weakest (by potential) among these 251 patterns is assimilated by its stronger (greater mass) nearest neighbor (n_k in the potential function). Assimilation consists of absorbing the mass of n_k and then deleting the weak pattern. The process repeats until all pixels in the data file have entered the competition. Ties can be broken in one of several reasonable ways.

Compared to the α-version, this process tends to locate more of the potential patterns in the regions of signal space that have greater pixel occupancy. Also, the masses of the potential patterns are predictive of the corresponding pixel patterns in the second stage which operates in the same manner as for the α-scenario. There is, however, a propensity to produce several patterns having low prominence in the second stage.

It may be desirable to have a summary measure for comparison, as for example the α-scenario versus the β-scenario, that can also serve to express overall strength of patterns extracted from an image. Since the competitive process in the first stage favors the (conditionally) stronger potentials, an obvious summary measure is total field potential of the patterns as given in Eq. 2.10,

$$\text{Pp.} = \sum \text{Pp}(k) \quad \text{or} \quad \sum \text{pP}(k) \tag{2.10}$$

according to whether pixel patterns or potential patterns are being considered. An entropy-based information-theoretic summary measure (Mirkin, 2005) for pattern prominence is the Shannon-Weiner index given in Eq. 2.11,

$$\text{Þp.} = - \sum (\text{p}_k)\ln(\text{p}_k) \tag{2.11}$$

where p_k is the prominence of the kth pattern in the lattice and ln denotes natural logarithm. It is readily seen that a pattern having low prominence contributes little to the latter index. Experimentation with a two-pattern case will show that this index favors evenness of prominences.

2.9 β-Scenario Splitting Stage

The choice of poles for the third stage of the α-scenario bears closer examination. The purpose of this third stage is to partition the sets of primitives from the second stage into subsets that are compact in signal space. Unless the high speed memory of a computer is massive, the major computational constraints revolve around transferring image and pattern information to and from lower speed memory devices such as disks. Therefore, preference is given here to approaches that avoid additional passes through large data files. In the multivariate (multiband) case, this disqualifies the more common statistical choices such as sum of squared distances from centroids.

The polar approach is expedient as long as all polar information can be obtained during a partitioning pass through the data. It seems intuitively reasonable that a good set of poles would be the pair of property points that are farthest apart in signal space (maximum diameter of the constellation). Unfortunately, however, this requires comparison of all possible pairs, which is computationally impractical for present purposes. A more expedient approach is to consider only pairs of poles that span the constellation in some sense.

The current sense of spanning is pairs of *peripheral points* according to the following concept. Let signal vectors (property points in signal space) P_1a and P_1b be taken as an initial polar pair, where P_1a has minimum norm and P_1b has maximum norm. Then replace either member of that polar pair by the most distant property point from its opposite pole (other than itself) as a new polar pair. Let each of a succession of such replacements also give a polar pair. Then define the set of all possible members of such polar pairs as being the set of peripheral property points (signal vectors).

The third stage of the α-scenario is based entirely on one such pair consisting of the points closest to and farthest from the origin of signal space ('darkest' and 'brightest', respectively). This pair is readily determined in the course of a partitioning pass through the data. The darkest and brightest elements are especially informative with respect to images, but they are not necessarily as effective with regard to obtaining compact constellations in signal space. It is quite possible that the dark-bright pole constitutes a relatively short diameter for a particular constellation. Likewise, the dark-bright pole has somewhat constrained directional variation in signal space over a series of subsets from successive partitions.

A modification can be made that makes the process of polar selection substantially self-correcting with respect to compact partitions, irrespective of the initial choice of polar pair. This modification retains the prior pole for each successive subset, and pairs it with the most distant point in the subset as its peripheral polar partner. Such polar pairs progressively pivot directionally through signal space in an unrestrained manner, thus providing opportunity for and tendency toward realignment with larger diameters of the constellations and thereby leading to more compact constellations over a series of subdivisions. The β-scenario incorporates this modification.

A possible further consideration for the third stage of the □-scenario is that of using the coordinates of the mid-pole position in signal space as a synthetic proxy for all the patterns in the nodal constellation. Despite the common practice of using averages for aggregations, it could be argued that an actual pattern should be preferred as a proxy over a synthetic one. A practical possibility in this regard is to use the actual pattern points that are closest to the prior quarter-pole positions. It may be noted that computation of mid-pole positions can be readily done retrospectively for comparative studies of the two methods.

The α-scenario has not had an overall measure for comparing complexity of constellations by which to track the trajectory of the third-stage splitting process through the successive cycles. A composite of the polar potentials of the nodal constellations can be formulated for this purpose. The utility for comparative purposes among images is improved by normalizing for both size of image and number of signal bands. Normalization for image size can be accomplished by using prominence of nodal patterns and normalization for signal bands can be done with number of bands as divisor. The composite complexity expression thus becomes Eq. 2.12,

$$Œ = (\sum p_k \Delta_k)/v \tag{2.12}$$

where

p_k is the prominence of the kth third-stage pattern;

Δ_k is axial (Euclidean) distance between poles;

v is the number of signal band values.

Since splitting reduces axial distance and increases compactness, the complexity coefficient must decline stochastically as splitting progresses. In general, greater complexity implies larger average errors in approximating primitive patterns of the image by proxies of polypatterns. The discussion by Breiman et al. (1998) of nodal impurity measures for classification trees is relevant in this regard. It may also be noted that a single-pixel pattern would contribute nothing to this measure by virtue of having zero as the axial distance.

2.10 Tree Topology and Level Loss

Since the third-stage splitting process is influenced by both prominence and axial distance, it is may be of interest to examine the structural topologies of the partitioning trees created in that stage. Relevant relations of nodal constellations to complexity and sub-structure can be indicated as a topological triplet in Eq. 2.13,

$$\textit{constellations:complexity:connection} \tag{2.13}$$

where *constellations* is the number of nodal constellations as terminals of the tree, *complexity* is the complexity coefficient as given above but with the summation limited to the particular tree, and *connection* is the maximum number of intermediate nodes between the root and a terminal.

The members of the topological triplet are informative both individually and in combination. A large number of constellations indicates substantial subdivision. The number of constellations in relation to connections indicates the degree of consistency in subdivision of subdivisions. A 'bushy' tree will have the number of constellations large in relation to the number of connections, or conversely for a 'spindly' tree that is tall and thin. The complexity in relation to number of constellations indicates propensity for further subdivision under additional splitting cycles. Comparing the complexity across trees is indicative of disparity in pattern complexity.

Determining the variability of the B-level proxies about the A-level proxies is informative relative to level-loss of specificity associated with using the A-level independently of the B-level. A natural way of assessing this is by mean squared error of prediction incurred by using A-level proxies as estimates of B-level proxies. This is computed as the sum of squared distances between B-level proxies and A-level proxies divided by the total number of B-level patterns. It also provides an index regarding sensitivity of the landscape pattern to generalization. The evenness of this information loss can be assessed by computing mean squared error separately for each A-level pattern, and then computing mean, variance, and coefficient of variation for these error data.

2.11 γ-Scenario for Parallel Processing

The α and β scenarios of polypattern processes have been considered implicitly for sequential computing environments. The extraction of bi-level poly-patterns is an extended operation in such computing environments, with computation times that can run into hours for larger images on conventional desktop PC computers depending on the number of bands and B-level splitting cycles. On the other hand, subsequent analyses of polypatterns proceed much more rapidly than for conventional image data since many computations can be done in the domain of pattern tables instead of spatial lattices. Therefore, production operations involving numerous large images would require that pattern extraction times be reduced by an order of magnitude through parallel computing and related intensive computing facilities. In the γ-scenario, we consider prospects for pattern processes that are amenable to parallel computing.

The first stage of α and β scenarios presents barriers to parallel computing by the sequential nature. Therefore, further generalization is necessary. This generalization can be envisioned as 'potential pattern pools'. A potential pattern pool is configured to accommodate some maximum number Y of potential patterns which would be operationally dependent on the number of signal bands in a pattern, but should be several multiples of the 250 in the α and β scenarios. Such a pool would reside in a processor and would function in 'fill and filter' cycles in conjunction with similar pools in other processors.

The 'fill' operation would ingest pixels from the next available position of the image data file until the pool is at capacity. The pool would then be 'filtered' down to some designated fraction of its capacity by successively assimilating the pattern having weakest potential into its stronger neighbor. The space thus made available in the pool would then be refilled until the several processors had collectively exhausted the image data file. The processors would then proceed to collaborate in pooling their partial pools until a single pool having the desired number of potential patterns was reached.

Aside from parallel considerations, a modification of this nature is effective in countering the tendency of the β-scenario to produce several patterns having low prominence. A pool containing excess patterns is carried to the end of the first stage, and the top 250 potential patterns in order of prominence are extracted for the second stage. A pool having an excess of 10% has proven to be workable in this regard.

In the second stage, the processors would all work with the final set of potential patterns, but would divide the image file into sections for compilation and then cross-compilation of (proxy) pixel patterns. In both the first and second stages, it would be possible to have the processors work either asynchronously or synchronously.

In the third stage, a 'bifurcation brokerage' queue would reside somewhere in the system, and the processors would operate individual 'bifurcation buffers'. The bifurcation brokerage queue would prioritize the nodal constellations for splitting. An individual processor would have its bifurcation buffer filled from the front of the queue and proceed to split those particular patterns while purging them from the queue. Upon completing a set of bifurcations, the processor would adjust the common queue so that the subsets would take their respective places according to their eligibility in terms of the splitting criteria.

The fourth stage would complete the segmentation scenario for parallel processing by allocating part of the lattice to each processor for the necessary nested numbering of patterns. As for the β-scenario, redistribution of prominence over A-level patterns would be an optional aspect.

It might seem that greater computing power would also favor extension from bi-level polypatterns to tri-level polypatterns. However, adding additional tiers causes eighth-power exponential growth in the number of trees of patterns with considerable computational overhead in cross-indexing the levels. A third level is marginally feasible, but using a two-byte second level would be more practical. Even so, the additional byte at the second level would tend to be unevenly exploited.

2.12 Regional Restoration

Restoration is accomplished by placing the proxy signal vector for the B-level of polypatterns in each pixel. The result is a 'smoothed' or 'filtered' version of the multi-band data having somewhat less variability than the original, due to removal of the intra-pattern variability. This will usually have some beneficial effect of making the data less 'noisy'.

Fig. 2.4 shows a restored version of band 2 for the September 1991 Landsat MSS image appearing in Fig. 1.1. The quality of detail in such restorations relative to the resolution of the original provides support for our claim that B-level of polypatterns can model image intensities sufficiently well to constitute an image compression for purposes of landscape analysis. Resolution of the image in Fig. 2.4 is constrained by the large size of pixels in the parent image that are 60 meters on a side.

2.13 Relative Residuals

Residuals from restoration are of interest not only for purposes of spatial statistics, but also for determining whether there are portions of the image area that have been restored with less fidelity than others. For the latter purpose, it is desirable to have an integrated measure of residual that incorporates the effects of all signal bands. This can be accomplished by using the Euclidean distance between the proxy signal vector for the B-level pattern and the actual signal vector for the particular pixel. Fig. 2.5 shows this kind of multiband residual image for the restoration in Fig. 2.4.

The spatial pattern in the residuals is of particular interest. An 'ideal' pattern would be one of uniformity, indicating that the errors of approximation were evenly distributed over the image area. The next most favorable pattern would be a random 'speckle' distribution indicating that the errors of approximation constitute 'white' noise relative to environmental features and locations. Typically, however, there is some nonrandom spatial patterning of the residuals. Then it becomes necessary to refer to the image itself to determine what kinds of environmental features have the least fidelity in their representation. In the case of Fig. 2.5, the fringe areas of clouds are prominent with regard to residuals. Since clouds are typically nuisance features in the image anyhow, this is not a matter of concern. The stronger discrepancies are due to the spectral and spatial complexity of cloud fringes.

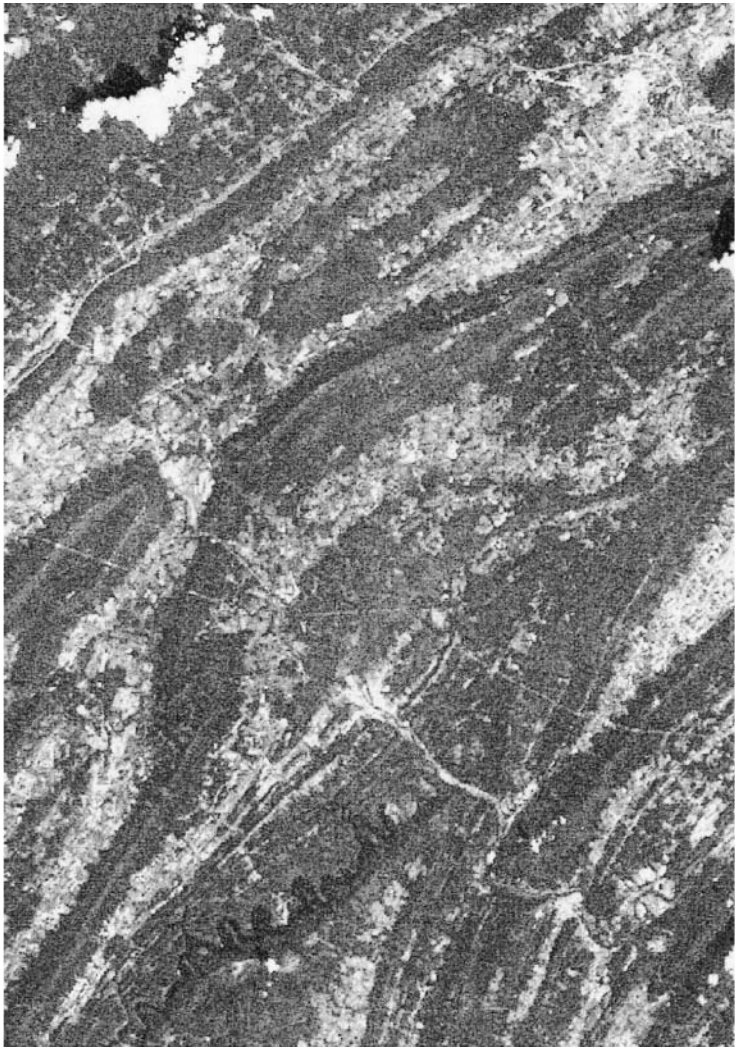

Fig. 2.4 Restored band 2 (red) of September 1991 Landsat MSS image of central Pennsylvania.

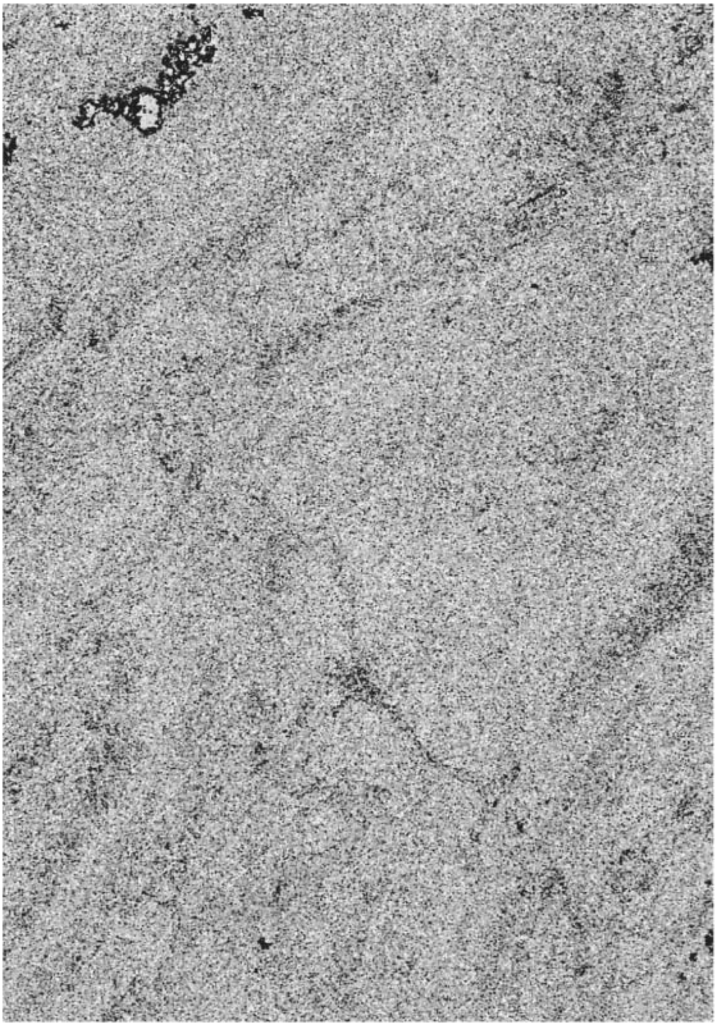

Fig. 2.5 Multiband residual image for September 1991 Landsat MSS image of central Pennsylvania with darker tones indicating larger residuals.

It is also interesting to examine how the depth of pattern splitting from A-level to B-level varies across the image in relation to the relative differences in residuals. Fig. 2.6 shows this aspect of the pattern-based image modeling, whereby lighter areas have more splitting. It can be seen that the darker areas indicating larger residuals in Fig. 2.5 correspond with the lighter areas indicating greater depth of splitting in Fig. 2.6. Therefore, continuation of splitting cycles would also tend to focus on these patterns that have higher internal variability.

In his comparative work on clustering for data mining, Mirkin (2005) emphasizes recovery of original information from clusters as being the touchstone criterion for efficacy of clustering methodology. Our methods of pattern analysis fall generally under the statistical heading of clustering, although they involve non-conventional modalities and have some non-conventional goals even among the many versions of clustering.

Recovery is one of our goals, which we address in terms of restoration from compression as set forth above. We are in a position to conduct a thorough assessment of recovery in terms of residuals, with regard to both form of statistical distribution and spatial dispersion of residuals as demonstrated in this chapter. We are also in a position of advantage by having the capability to improve recovery through additional cycles of splitting if the residuals are deemed to be excessive.

In perhaps a somewhat counter-intuitive manner, we derive benefits from an assurance of less than complete recovery. One such benefit arises from avoiding exact electronic duplication of image data that may carry concerns for their proprietary nature. Our methodology produces image intensity models. The B-level patterns constitute a discretely valued model of the original image, and the A-level patterns provide a more generalized (less specific) model. Together, these models support multi-scale landscape analysis as well as selective enhancements for graphic emulations of pictorial images.

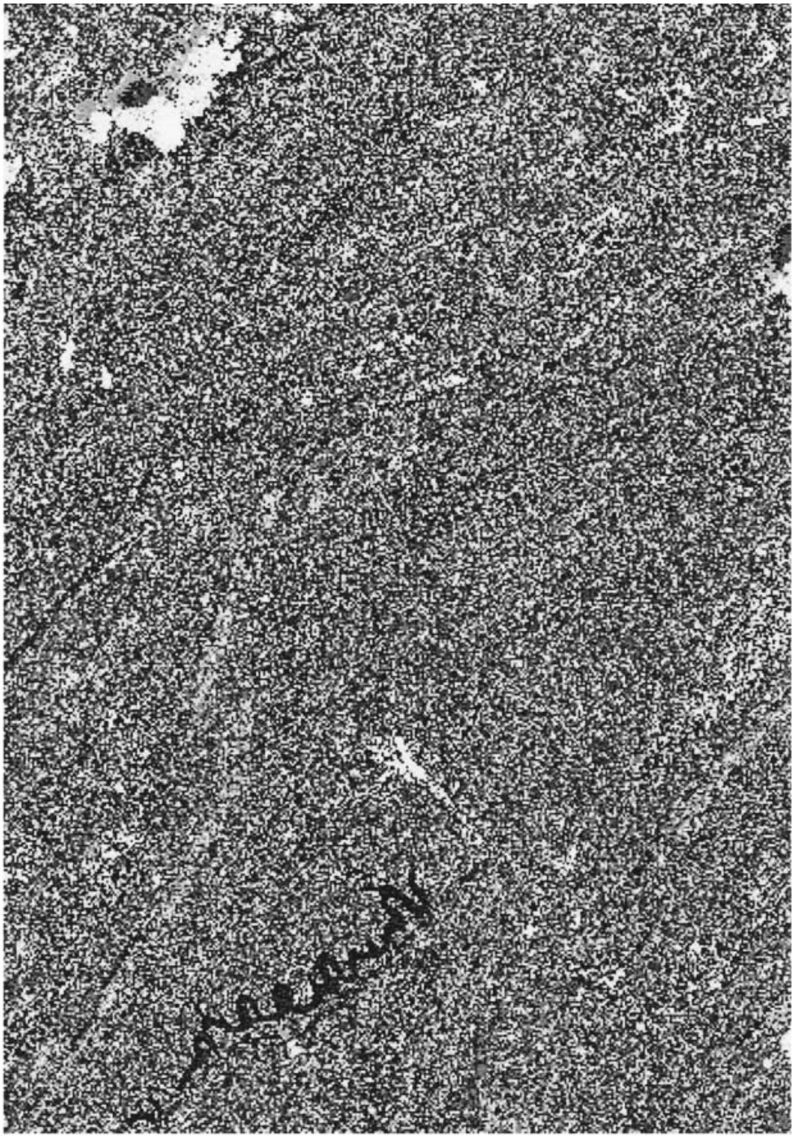

Fig. 2.6 Distribution of depth of splitting from A-level to B-level pertaining to residuals in Fig. 2.5 with lighter tones showing greater splitting.

2.14 Pictorial Presentation and Grouped Versus Global Enhancement

Direct display of A-level indexes as ordered overtones has been introduced earlier. Pictorial presentation of particular pattern properties involves triple indirection whereby look-up tables of pattern properties are used to prepare look-up tables of relative intensities that are used to prepare look-up tables that specify coloration for patterns. Since all of three of these tables are subject to change, there is a great deal of flexibility in the manner that patterns are portrayed. This makes possible enhancements of presentation graphics that cannot be obtained through conventional image analysis.

Enhancement is an image analysis term for operations that are applied to pixel properties in order to obtain pictorial presentations wherein certain aspects have more evident expression. In conventional image analysis, enhancement operations are applied globally to all pixels. Pattern presentations permit greater specificity whereby enhancement operations are applied selectively to a particular pattern or groupings of patterns, thereby avoiding alterations of the entire image. This even extends to generalizing the perception of patterns by displaying similar patterns the same to give them identical appearance. This is a considerable convenience for initial investigation of multi-scale characteristics of landscapes.

Appendix A suggests software that can be procured publicly without purchase for pictorial presentation of patterns. Since patterns are at least in part a perceptual pursuit, preliminary perusal of presentation protocols is prudent.

2.15 Practicalities of Pattern Packages

A prototype package for pattern processing is introduced in Appendix B. This is a modular package developed in generic C language to promote portability among platforms for computing. Specifications are submitted by editing a standard text file, which is then read by the respective module. The text file also contains imbedded instructions for making the appropriate substitutions. A Windows-style 'front-end' is also available as an alternative mode of managing most modules under Microsoft supported systems. The A-level of polypatterns is presented as byte-binary image information in a file having .BSQ extension, along with companion compilations of characteristics as textual tabulations in separate files. The B-level of polypattern information resides in a byte-binary file having .BIL extension, along with supporting tabulations that are also byte binary. Complete comprehension of the ensuing chapters may require reference to this software supplement, and even perhaps practice.

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