MODELING MULTISCALE LANDSCAPE STRUCTURE WITHIN A HIERARCHICAL SCALE-SPACE FRAMEWORK

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Commission IV, WG IV/6

KEY WORDS: Hierarchy theory, Scale-Space, Multiscale Landscape Structure, Blob-Feature Detection, 3D-Visualization

ABSTRACT:

In this paper we describe a novel integration of Hierarchy Theory and Linear Scale-Space for automatically visualizing, and modeling dominant landscape structures at multiple scales. Specifically, we describe 3D methods for modelling and visualizing *landscape scale-domains* by using scale-space events as *critical domain thresholds*. This novel approach provides the capacity to automatically define dominant landscape structures within varying shaped scale domains, as well as through (all) domains. We hypothesize that the resulting domain structures represent critical landscape scale thresholds; which could be used as templates to define the grain and extent at which scale-dependent ecological models could be developed and applied, and the limits over which landscape data may be uniquely scaled.

1. INTRODUCTION

Landscapes are complex systems that are composed of a large number of heterogeneous components that interact in a non-linear way, are hierarchically structured, and scale dependent (Wu and Marceau, 2002). Remote sensing technology represents the primary provider of such landscape-sized data. Therefore, if we are to fully understand, monitor, model, and manage our interaction within landscapes, we require a multiscale framework capable of incorporating appropriate multiscale-theory and techniques to extract dominant landscape components from remote sensing data at their specific scales of expression (Marceau and Hay, 1999; Hay et al, 2002b). However, this is no trivial task. The notion of 'landscape' varies between users, there is no 'science of scale', nor are there fixed scaling laws or rules for translating data between scales (Hay et al, 1997). In most cases we do not know the 'correct' scale for collecting remote sensing data at, but rather, are limited to resolutions defined by the state of sensor technology (i.e., spatial, spectral, temporal, radiometric). Furthermore, once we do acquire data, how and where we scale to and from is often arbitrarily defined (Hay et al, 2001). In an effort to reduce these challenges, we describe a novel framework that integrates *Hierarchy theory* and *Scale-Space* (SS) for automatically visualizing and modeling dominant landscape structures through multiple scales, and within uniquely defined scale domains. In particular, the primary objective of our study is to automatically link structures at unique scales in scale-space, to higher-order objects called *'scale-space blobs'*, and to extract significant features based on their appearance and persistence through all scales. Blob-like structures, which persist in scale-space, are likely candidates to correspond to significant structures in the image, and thus in the landscape. In addition, by considering scale-space events as critical domain thresholds, we are able to three-dimensionally model and visualize multiple 'landscape scale-domains'. This novel approach provides a new capacity to automatically define dominant landscape structures within varying shaped scale domains, as well as through (all) domains. We hypothesize that these domain structures represent critical landscape scale thresholds; thus they may be used as templates to define the grain and extent at which scale-dependent ecological models could be developed and applied, and the limits over which landscape data can be scaled.

In general terms, a *hierarchy* may be defined as 'a partial ordering of entities'; thus hierarchies are composed of interrelated subsystems, each of which are made of smaller subsystems until a lowest level is reached. Within the formal framework of Hierarchy theory (Allen and Starr, 1982), a hierarchically organized entity can be seen as a three-tiered nested system in which levels corresponding to slower behavior are at the top (Level +1), while those reflecting successively faster behavior are seen as a lower level in the hierarchy (Level -1). The level of interest is referred to as the Focal level (Level 0). From a Landscape Ecology perspective, Hierarchy theory predicts that complex ecological systems, such as landscapes, are composed of relatively isolated levels (*scale domains)*, where each level operates at relatively distinct time and space scales. *Scale thresholds* separate these domains, and represent relatively sharp transitions or critical locations where a shift occurs in the relative importance of the variables influencing a process. In general, interactions tend to be stronger and more frequent *within* a domain than *among* domains. Conceptually, these ideas enable the perception and description of complex systems by decomposing them into their fundamental parts and interpreting their interactions.

2. METHODS

2.1 Study Site

Due to the computational demands required by SS processing, analysis was performed on a high-resolution (1.0 m) panchromatic IKONOS image (acquired in September, 2001) that was linearly contrast stretched from 11- to 8-bits. A 2.0-km^2 sub-area was then extracted and upscaled to 4.0 m using Object-Specific Upscaling (Hay et al, 2001). Geographically, this area represents a highly fragmented agro-forested landscape in the Haut St-Laurent region of south-western Québec (Bouchard and Domon. 1997).

2.2 Linear Scale-Space (SS) and Blob-Feature Detection

All multiscale analysis is composed of two main components: the generation of a multiscale representation, and a feature detector. *Linear Scale-space* (SS) is used for generating a multiscale representation. Essentially, SS is an uncommitted framework for early visual operations that was developed by the computer vision community to automatically analyze real-world structures at multiple scales – specifically, when there is no *a priori* information about these structures, or the appropriate scale(s) for their analysis (Lindeberg, 1994). The term *uncommitted framework* refers to observations made by a front-end vision system (i.e., an initial-stage measuring device) such as the retina or a camera that involves 'no knowledge', and 'no preference' for anything. When scale information is unknown within a scene, the only reasonable approach for an uncommitted vision system is to represent the input data at (all) multiple scales. Thus, the basic premise underlying SS is that a multiscale representation of a signal (such as a remote sensing image of a landscape) is an ordered set of derived signals showing structures at coarser scales that

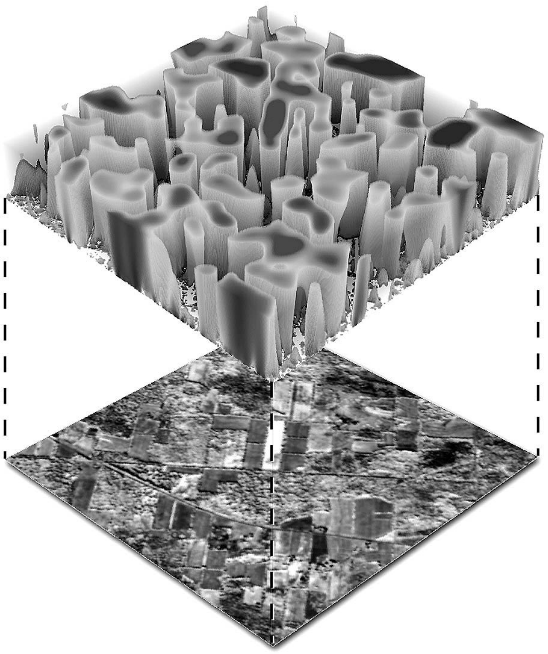

Figure 1. This illustrates a linear scale-space stack composed of 200 scales. The smallest scale is on the bottom; the largest is on the top. Note the diffusive patterns and persistence of scale-space objects through scale. For reference, the 500 x 500 pixel Ikonos image is also provided (bottom).

constitute simplifications of corresponding structures at finer scales. In practice, Gaussian filters are applied to an initial image at a range of kernel sizes resulting in a scale-space cube or 'stack' of progressively 'smoothed' image layers, where each new image layer represents convolution at an increased scale (Fig. 1). More explicitly, each 'smoothed'

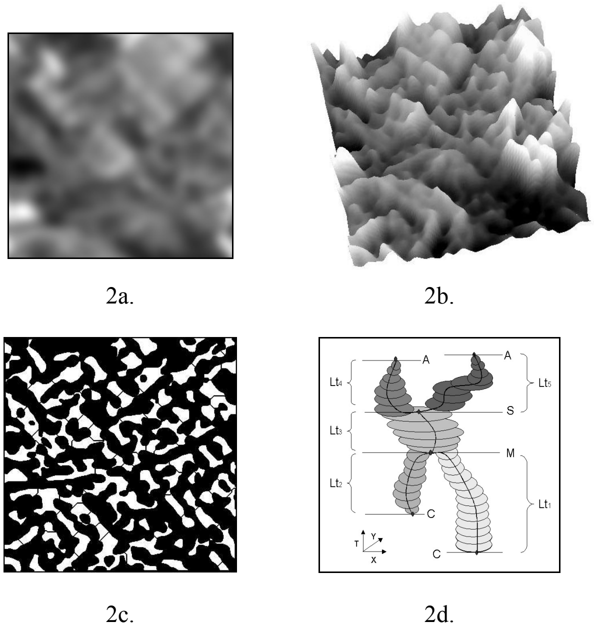

Figure 2a. 2D Grey-level blob at scale 20. (2b) 3D Grey-level blobs illustrated as a topographical surface from which a blob-delineation watershed analogy is described (scale, 20). (2c). Binary blob defined from 3a. (3d) Idealized hyper-blob illustrating four different SS-events: annihilations (A), creations (C), merges (M) and splits (S). The number of scales between SS-events represents the lifetime (Lt_n) of a SS-blob.

layer is created by convolving the n^{th}-order *derivative of a Gaussian* (DOG) function with the original image, where the scale of each derived signal is defined by selecting a different standard deviation for the DOG function (at each new iteration). In the presented work we have only use the $zero^{th}$ order derivative. This results in a 'scale-space cube', or 'stack' of increasingly 'smoothed' images, which illustrates the evolution of the original image through scale. Each hierarchical layer in a stack represents convolution at a fixed scale, with the smallest scale at the bottom, and the largest at the top.

Blob-Feature Detection represents the second component of multiscale analysis. The primary objective of this non-linear approach is to link structures at different scales in scale-space, to higher-order objects called 'scale-space blobs', and to extract significant features based on their appearance and persistence over scales. The main features that arise at each scale within a stack are smooth regions, which are brighter or darker than the background and which stand out from their surrounding. These regions are referred to as 'grey-level blobs' (Fig. 2a). When blobs are evaluated as a volumetric structure within a stack, it becomes apparent that some structures visually persist through scale, while others disappear (Fig. 1). Therefore, an important premise of SS is that blob-like structures which persist in scale-space are likely candidates to correspond to significant structures in the image, and thus in the landscape. In simple terms, grey-level blobs at each scale in the stack are treated as objects with extent both in 2D space (x, y) and in grey-level (z-axis) – thus 3D. Grey-level blob delineation may best be defined with a watershed analogy.

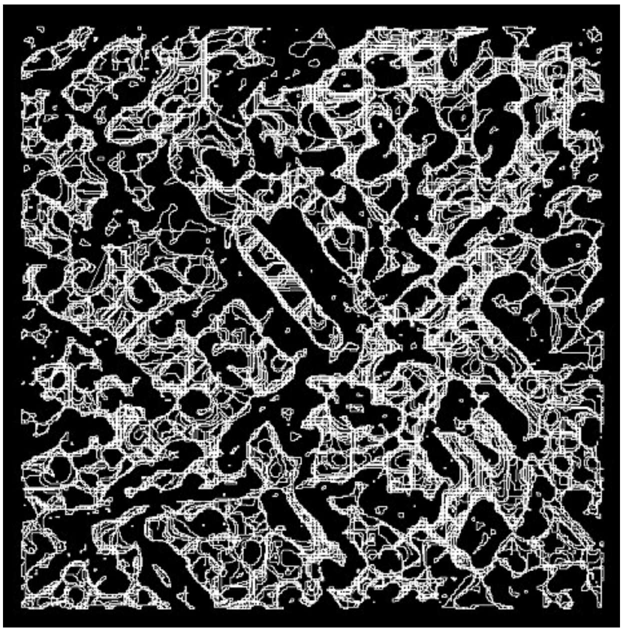

Figure 3. Ranked blobs converted to individual queriable vectors. Note how polygons from many different scales appear to overlay each other making analysis non-trivial.

At each scale in the stack, the image function of all blobs may be considered as a flooded 3D landscape (i.e., a watershed see Fig. 2b). As the water level gradually sinks, peaks appear. At some instance, two different peaks become connected. The corresponding 'connected' elevation levels are called the 'base level' of the blob. They are used for delimiting the 2D spatial extent or 'region of support' of each blob, which is defined as a binary blob (Fig. 2c). 2D binary blobs at all scales are then combined within a new stack to create 3D hyper-blobs. Within a single hyper-blob there are four primary types of visible structures or 'bifurcation events': *annihilations* (A), *merges* (M), *splits* (S), and *creations* (C) (Fig. 2d). The ability to define these SS-events is a critical component of SS, as scales between bifurcations are linked together forming the lifetime (Lt_n) and topological structure of individual SS-blobs. Next, the integrated normalized (4D) volume (x, y, z, t) of each individual SS-blobs is defined.

As blob behavior is strongly dependent upon image structure, it is possible that an *expected* image behavior may exist. Thus statistics are extracted from a large number of stacks resulting from random images[1]. These statistics describe how random noise blobs can be expected to behave in scale-space, and are used to generate a normalized 4D SS volume for each SS-blob.

These resulting normalized volumes are then ranked, and an arbitrary number of significant SS-blobs are defined, from which the scale (t) representing the maximum 3D grey-level blob volume (x, y, z) of each hyper-blob is extracted. From these layers the 2D spatial support (i.e., binary blob) is identified and related back to the corresponding structures in the image for further examination (Fig. 3). Thus, based on the underlying initial premise, 4D scale-space blobs are simplified to 3D grey-level blobs, which are further simplified to their 2D support region (x, y), and then to their corresponding real-world object in the original image. For a more detailed non-mathematical description of SS and Blob-Feature Detection, see Hay et al., 2002a.

2.3 Integrating Hierarch Theory and Scale-Space

A limitation of SS is that within a SS-cube a significant amount of redundant data results in large stack sizes, which in our research range from 200 MB to 980 MB each. In order to reduce the memory requirements when defining SS-blob topology, we have integrated a three tier approach from Hierarchy theory with the programming capability of IDL (interactive data language) to 'parallel-process' multidimensional array structures. Thus, instead of loading the entire stack into memory, we only need to load three scales of a SS-cube into memory at a time. From a Hierarchy theory perspective, we evaluate the blob locations at the 'focal' scale, and establish links with blobs in the scale above and with those in the scale below. We then shift up an additional scale in the cube, while dropping the bottom scale. Always keeping only three scales in memory at once. We then repeat this procedure until the last scale has been processed.

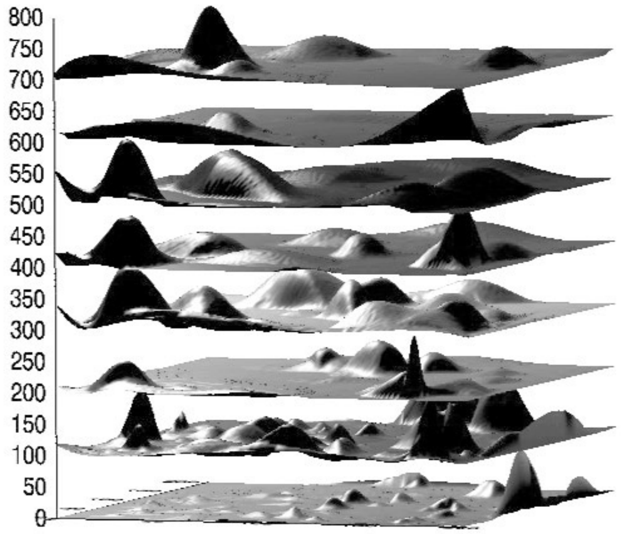

Figure 4. This is an example of 8 threshold-domain surfaces visually modeled from a stack of 100 layers (thus the value 800 in the scale axis), and an x, y dimension of 200 x 200 pixels. Each domain layer is modeled one above the other for visual interpretation. Each domain surface stacks exactly upon the surface underneath it, with no peak protruding into the upper or lower surface. Peak locations represent the bifurcation point of each scale-space blob defined within a single hyper-blob.

In order to overcome evaluation problems resulting from the large number of ranked SS blobs that visually obscure each other when overlaid on the study area (Fig. 3), we suggest that SS-events represent critical thresholds within a hyper-blob, where fundamentally different geometric structures exists both in scale and the landscape. Thus from an ecological perspective, the lifetime of a SS-blob may be

[1] In our processing we generated 100 individual stacks resulting from different random images the same size as the original 500 x 500 pixel IKONOS image. Each random SS stack was composed of 200 layers with a scale increment of one.

considered as levels within a specific scale-domain. To define this domain, each hyper-blob is topologically registered as a unique entity, and its corresponding SS-events are isolated. That is, the first SS-event of all hyper-blobs are geometrically defined regardless of where, and what scale they exist within the stack (i.e., x, y, t). Then the second, third, and n^{th}-events of each hyper-blob are isolated until the last possible event is defined. These event values are then considered as 'scale domain attributes' and are assigned to their corresponding ranked blobs. This domain attribute provides a unique way to query, partition, and evaluate the resulting multiscale 'domain' surface structures, as many blobs can and do exist within a single domain, but no more than one blob can exist within the same 'x, y, z, domain' space. Thus the problem of overlapping ranked blobs is resolved (Fig 3.) and it allows us to evaluate the resulting multiscale surface structures in terms of *critical scale-specific thresholds*.

In addition, by integrating these hierarchical concepts with geostatistics and 3D visualization techniques, domains can be visually modeled as 'scale-domain manifolds'. To visualize these domain structures, we define the center pixel of each bifurcation blob, apply Delaunay triangulation to all points, and then interpolate with a Quintic polynomial function to generate a smooth surface [Fig. 4 - see Hay et al, (2002b)]. Furthermore, we suggest that this structure correspond to the 'scaling ladder' as conceptualized by Wu (1999) in his description of the Hierarchical Patch Dynamics Paradigm.

3. CONCLUSION

In this paper we describe a novel integration of Scale-Space and Hierarchy Theory for automatically visualizing, defining and modeling dominant landscape structures at multiple scales. Scale-space originates from the computer vision community, where it was developed to analyze real-world structures with no *a priori* information about the scene being assessed. Its basic premise is that a multi-scale representation of a signal (such as a remote sensing image of a landscape) is an ordered set of derived signals showing structures at coarser scales that constitute simplifications of corresponding structures at finer scales. The primary objective of our study has been to define and link structures at different scales in scale-space to higher-order objects, called "scale-space blobs", and to extract significant features based on their appearance and persistence over all scales. Blob-like structures, which persist in scale-space, are likely candidates to correspond to significant structures in the image, and thus in the landscape. Furthermore, by integrating concepts from Scale-Space and Hierarchy Theory, we are able to three-dimensionally model and visualize multiple 'landscape scale-domains' based on the novel idea of using scale-space events as critical domain thresholds. This novel approach provides the capacity to automatically define dominant landscape structures within varying shaped scale-domains, as well as through (all) domains. Spatial statistics are used to describe these significant landscape structures, and 3-D tools have been developed to visualize and describe their multi-dimensional morphology. Our next objective is to ascertain relationships between the dominant patterns within each domain, and the (potential) processes that formed them, in order to better understand the multi-scale dynamics of this landscape, and to evaluate the efficacy of the integrated theory and techniques.

4. ACKNOWLEDGEMENTS

This work has been supported by a team grant from FCAR, Gouvernement du Québec, awarded to Dr. André Bouchard and Dr. Danielle Marceau, and by a series of scholarships awarded to Mr. Hay which include a Marc Bourgie Foundation Ph.D. Award of Excellence, a Biology graduate scholarship of excellence from the University of Montréal, and a GREFi Ph.D. scholarship (*Groupe de recherche en écologie forestière interuniversitaire*). We also thank Mr. Patrick Dubé for his assistance with scale-space coding.

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