A Multi-Scale Model of Perceptual Organization in Information Graphics

Martin Wattenberg
IBM Research
mwatten@us.ibm.com

Danyel Fisher
School of Information & CS
University of California, Irvine
danyelf@acm.org

Abstract

We propose a new method for assessing the perceptual organization of information graphics, based on the premise that the visual structure of an image should match the structure of the data it is intended to convey. The core of our method is a new formal model of perceptual structure, based on classical machine vision techniques for analyzing an image at multiple resolutions. The model takes as input an arbitrary grayscale image and returns a lattice structure describing the visual organization of the image. We show how this simple model captures several aspects of traditional design aesthetics, and we describe a software tool that implements the model to help designers analyze and refine visual displays. Our emphasis here is demonstrating the model's potential as a design aid rather than as a description of human perception, but given its initial promise we propose that it merits further study and describe a variety of ways in which the model could be extended and validated.

Keywords: Visualization, Perceptual Organization, Scale Space, Design Methodology

1 Introduction

The design of information visualization software remains a poorly understood, hit-or-miss process. Part of the difficulty is that models for how humans extract information from visual displays remain incomplete. Indeed, seemingly minor design variations can have dramatic effects on comprehensibility. As a result, creating effective displays often requires expensive user tests, time-consuming redesigns, and even a certain amount of guesswork.

Many researchers have recognized these problems and have investigated guidelines and models for the perception of information graphics. Much work has been done on the efficacy of different visual encodings (e.g. [Cleveland 1980, Mackinlay 1988]), resulting in useful rules about the use of color, position, area, etc. to represent different types of variables. Others, for example [Healey 1993], have investigated how models of preattentive processing can be used in designing visualizations.

But these lines of research do not address a key element in the efficacy of an information graphic: the degree to which its perceptual organization reflects the organization of the underlying data. Many authors have stressed that to design successful information graphics one must take into account the effects of perceptual grouping. For instance, [Kosslyn 1989] contains many examples in which unintentional grouping effects lead to confusing displays. It would therefore be useful to have a tool that helped designers assess the perceptual organization of their designs

Some attempts have been made to model perceptual organization in information graphics. Tufte provides general guidelines, such as the "Macro/Micro" principle [Tufte 1990]. But quantitative models suitable for software implementation are rare. Several authors have analyzed special classes of displays: [Tullis 1984] analyzes alphanumeric screens; [Shneiderman et al. 1995] investigate standard Visual Basic dialog boxes. The work of [Saund 1990] on deriving perceptual structure in the context of sketch editing is more ambitious, but still requires a vectorized version of a graphic as input. Because it is not amenable to the analysis of non-vector-based visualizations, it is problematic to apply his method to the output of existing programs.

In this paper we introduce a new formal model of visual organization which can be applied to a broad class of information graphics. We present an algorithm that takes as input an arbitrary grayscale image, and returns as output an analysis of the image's organization that links perceived structures at different scales. We then describe a prototype software tool that applies this model to help designers see how an information graphic may be understood. We demonstrate the utility of the model by exhibiting a variety of examples in which it captures aspects of design aesthetics; we also show how it can be used in the redesign of a real-life visualization. Finally, we discuss directions for validating and extending the model.

2 A Multi-Scale Model of Visual Organization

2.1 Motivation: Importance of Multiple Scales

Most information graphics display structure at several different scales. That is, an image will contain large-scale organization as well as many smaller details. Our hypothesis is at all these scales the visual structure should reflect the structure of the data being conveyed, with large-scale organization reflecting a broad overview or summary, and smaller details reflecting details of the data. As [Bertin 1983] puts it:

> *A graphic should not show only the leaves; it should show the branches as well as the entire tree. The eye can then go from detail to totality and discover at once the general structure and any exceptions to it.*

This intuition about multiple scales is shared by many visual designers. Typographers, for example, routinely speak of a visual hierarchy in text layouts. Figure 1 shows a hand-drawn example of such a hierarchy. (We have chosen a piece of text as an example for analysis in the next section since it has several natural, unambiguous scales: letter, word, line, and paragraph.)

Despite the general belief that multi-scale structure exists and is important, that structure can prove surprisingly elusive. Even experienced designers will resort to tricks such as looking at image from across a room or holding it upside down to get a better sense of its organization. In many ways it would be helpful to have a mathematical model that matched the standard designer's intuition. Such a model could be useful to designers, for instance, who could apply it to early designs to see if the structure matched what they wished to communicate. It could also be helpful in automating some aspects of design—for instance, a computer might try to use the model to optimize the correspondence between visual structure and data structure. All of these potential uses rely on a precise model that can implemented algorithmically.

2.1.1 Human and Machine Vision

Psychologists have long studied perceptual organization and its multi-scale aspects. A full review of the psychological literature on this topic is beyond the scope of this paper, but we cite a few reference points. Gestalt psychologists, starting with Wertheimer [1924], have proposed a number of "laws" for how the brain groups objects: by proximity, good continuation, and so on. Multi-scale aspects of grouping have also been addressed in several lines of research (e.g. [Palmer 1977], [Navon 1977]). Many of these theories of grouping were qualitative, but investigators have worked on creating quantitative or algorithmic models as well. Typical examples from this large research area are [Kubovy 1994], who treats grouping by proximity in dot lattices, and the work of Li [1998] on neural network simulations of cortical processing.

The quantitative psychological models cited above are, unfortunately, highly specialized and not instantly applicable to the task of analyzing information graphics. (It's a long way from dot lattices to graphs, charts, and treemaps.) The field of machine vision, however, provides a different and more immediately fruitful perspective. Analyzing visual structure has long been recognized as an important component of computer vision (see [Witkin and Tenenbaum 1983]), and modern computer vision frameworks typically are designed to be applied to arbitrary images. In this paper we highlight one particular framework, scale space theory, and through a series of examples suggest that it is particularly suitable for the analysis of information graphics. A natural future direction would be to reconnect this model with psychological work through experimental validation.

2.2 Limits and Assumptions

Rather than attempting to model the full range of visual experience, we focus on non-interactive motionless grayscale images, and make no attempt to reconstruct a 3D scene. By eliminating from consideration color, depth, motion, and interactivity we simplify the domain considerably yet retain significant generality, for example encompassing a significant fraction of printed information graphics. Obviously it would be desirable to have a model that eventually did account for these other dimensions, and in the final section we discuss potential generalizations.

2.3 Our Model: Mathematical Definition

We now define our model. First we make precise the idea of "scale." Then we define a simple method of extracting structure at a given scale. Finally we describe a technique for linking structures found at different scales.

2.3.1 Scale Space

We base our model on the classical machine vision concept of *scale space*. Scale space theory [Iijima 1959, Witkin 1983, Koenderink 1984, Lindeberg 1994] is a formalism that describes the structure of a signal at many different scales at once.[1]

[1] Despite the similar name and notation, scale space in this sense is not directly related to the "space-scale diagrams" of Furnas and Bederson [1995], an elegant application of Riemannian geometry to zooming user interface design.

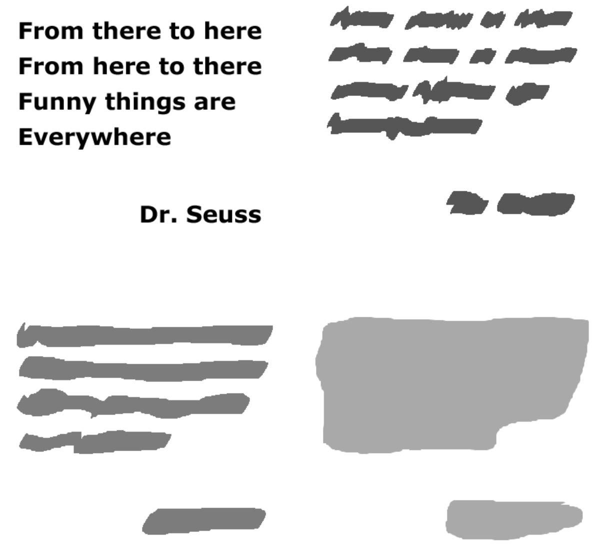

Figure 1. Visual hierarchy, hand-drawn, for a piece of text. (The "Dr. Seuss" image.)

To define scale space precisely, we need some notation. First, we represent the input image as a function:

$$f: [0,1] \times [0,1] \rightarrow [0,1].$$

That is, we take f to be a function on the unit square, where a value of 0 corresponds to black, 1 to white, and values in between correspond to shades of gray.

Given the function f, we then extend its domain to a 3-dimensional "scale space" by a special family of functions f_s where s ranges from 0 to 1. First, let G_s be a Gaussian kernel with "width" s; more formally, let

$$G_s(x,y) = \exp\left(-(x^2+y^2)/2s^2\right) / 2\pi s^2$$

We define then f_s by

$$f_s = f * G_s$$

where * represents convolution. Informally, the function f_s represents the original image having been blurred by a factor of s. Figure 2 shows f_s for three different values of s. The 3-dimensional space formed by the spatial dimensions x,y and the new scale dimension s is known as scale space, and by analyzing the functions f_s on this 3-dimensional scale space we can get at important structures in the original 2-dimensional image.

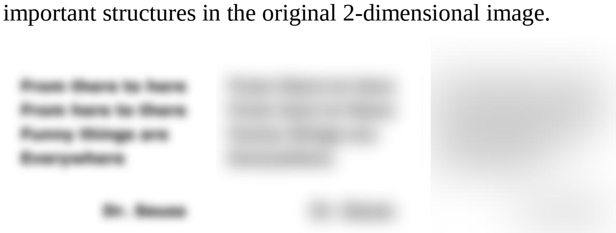

Figure 2. f_s for the Dr. Seuss image, where s=8, 16, 44.

2.3.2 Structure and segmentation

Having defined scale space we now need a notion of structure or organization at a given scale. There are many possible ways to define a structure. We choose to define structure by creating a segmentation of the image at each scale. For a given scale *s*, we follow Marr and Hildreth [1980] and consider the difference-of-gaussians edge detection function

$$g_s = f_s - f_{3s/2}.$$

This function is one of the best studied edge detectors, and has some correspondence to the responses of retinal neurons. It is a close approximation of another classical edge detector, the Laplacian operator, but numerically more stable. Figure 3 shows the function g_s for the Dr. Seuss image at three different scales.

Figure 3. Difference of Gaussians: f_s-$f_{3s/2}$, s=8,16,44. 50% gray is zero; dark gray is negative; light gray is positive.

We can then naturally segment the unit square into regions where $g_s \neq 0$. The connected components of these regions form the elements of our segmentation. The sign of g_s also has significance; its corresponds, very roughly, to whether the segment is brighter or darker than its neighbors.

Why use the difference-of-gaussians edge detector? It has several advantages. First, simplicity: it is well-understood and efficient to calculate. Second, unlike several other popular edge detectors (e.g. [Canny 1986] or [Shen and Castan 1992]), the difference-of-gaussians method has the benefit of immediately producing closed contours, thus creating a segmentation without additional steps. Third, the sign of the function g_s is useful in creating an algorithmic version of the linking step below. Despite these advantages, it is important to note some well-known drawbacks to this technique: poor localization, rounded corners, oversensitivity [Parker 1997]. A different edge detector would not, however, fundamentally alter the framework of our model.

Figure 4 shows the resulting segmentation at scales of 8, 16, and 44. In the top row the edges of segments are shown. In the bottom row, each segment has been filled with a single gray tone representing the average grayscale value of the pixels in the segment, a technique we call a *Gestalt cartoon*. (This in itself is a small but interesting visualization issue: informal tests showed that for complex segmentations, users found these Gestalt cartoons easier to interpret than an outline view.) Note how closely the images in the bottom row match the intuitive hand-drawn diagrams of Figure 1.

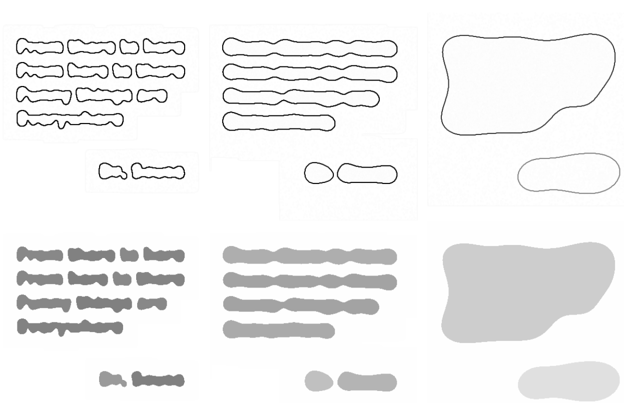

Figure 4. Algorithmically derived segmentation of the Dr. Seuss image for *s*=8,16,44. Top: edges of segments. Bottom: filled segments, or *Gestalt cartoons*.

Edge detection is not the only way to locate structure at a given scale. Probably the most common method—one used in many of the original scale space papers—is to analyze local maxima and minima of the function f_s [Witken 1983, Koenderink 1994]. Often this analysis is accompanied by some sort of watershed segmentation [Lindeberg 1994, Leung et al. 2000]. We tried several variants of this technique but found they produced poor results, possibly due to the non-generic nature of typical information graphics. Compared to images of natural scenes, diagrams and visualizations have an unusual number of areas of uniform brightness. In many cases we found that the graph of f_s contained ridges, valleys, and plateaus that were almost but not quite level, leading to a proliferation of local extrema that did not correspond to useful features in the image. This is why we chose the edge-detection scheme described above.

2.3.3 Linking structures at different scales

As described so far, the model finds structure only at a single scale. But the perceptual structure of an image includes not just the structure at one scale, but the relationships between features at different scales. In the scale space literature, linking features between scales is often referred to as finding the *deep structure* of an image [Koenderink 1984]. In this section we describe a novel method of finding this deep structure that is particularly useful for information graphics.

Consider the segmentations in Figure 5, shown as a series of Gestalt cartoons. It is visually clear that the two blobs in the *s*=11 view correspond to the individual letters of the words "Dr." and "Seuss" respectively. The final part of our model is a method of making this intuition precise.

Figure 5. Four scales of Dr. Seuss

Let S_1 and S_2 be two image segments found at scales $s_1 \leq s_2$ respectively. We can naturally view S_1 and S_2 as embedded within the 3D scale space, i.e. as the sets $\{s_1\} \times S_1$ and $\{s_2\} \times S_2$. We will say S_1 is *linked* to S_2, denoted by $S_1 \leq S_2$, if either $S_1 = S_2$ or there is a path through scale space from a point on S_1 to a point on S_2, such that g_s maintains the same sign and *s* is monotonically increasing. It is easy to verify that the relation "≤" defines a partial order on the set of segments. It is also clear from the definition that this partially ordered set breaks into two disconnected components, one that corresponds to the subset of segments where $g_s<0$, which we denote as L^- and one we call L^+ where $g_s>0$. (It is possible for each of these two sets to have many maximal elements.) In some cases, L^- and L^+ turn out to correspond to foreground and background elements. For example, in the Dr. Seuss image, the segments corresponding to the text are represented in L^- while the whitespace is represented in L^+.

Figure 6. Linked segments in L^- at different scales for part of the Dr. Seuss image.

Figure 6 is a visualization of the results of connecting linked segments in L^- for the Dr. Seuss image.

The image shows a 3D view of scale space, with five separate planes highlighted (corresponding to s=1,4,7,11, and 14). For each plane, we show the segmentation for the corresponding s value, and for each pair of linked segments in adjacent planes we have drawn a line between the segments' centroids. For simplicity, in this diagram we only show L^-, the segments with positive g_s, since they account for the main visual structure. The result is a tree structure on the words that corresponds to the intuitive hierarchical division of a phrase into words and words into letters.

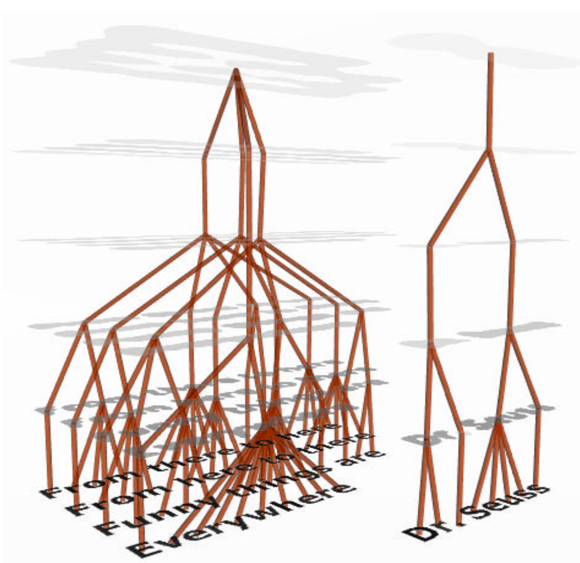

Figure 7. The linked structures in L^- for the entire Dr. Seuss image are shown in orange.

The choice of a 3D display is a visualization exercise in its own right. We tried various alternatives, such as abstract graph-theoretic views of the lattice and a layout of 2D thumbnails with connections drawn between segments. In these cases, however, users were uniformly confused about the connection between the lattice structure and the image.

For completeness the L^- lattice for the entire Dr. Seuss image is shown in Figure 7. Again, the structure nicely corresponds to the intuitive hierarchy of paragraphs, lines, words, and letters.

Although linking structures at different scales by following zero-crossings of various operators is common in scale space theory [Lindeberg 1994], the particular linking described here is unusual, and in fact is a key distinguishing feature of our model. Most scale space segmentation algorithms seek a hierarchical segmentation of an image, where the partial order is always a tree structure. The segmentation described above, however, can produce non-nested segments with non-tree lattices. In the context of scene segmentation and object recognition—the conventional applications of scale space theory—this is an undesirable property. But as several authors have pointed out [Saund 1990, Leung et al 2000], a non-tree lattice seems to model well the visual experience of certain images. Indeed, given that the goal of many information graphics is to portray complex interrelationships, any model that led to pure trees would be of limited applicability.

Figure 8 gives an example of an image whose visual structure is not tree-like. The barbell image, at a small scale, is one continuous object, at a slightly larger scale breaks into two main parts, and at a large scale merges into one object again.

2.3.4 Related Methods

The general concept behind our construction, analyzing a signal at multiple resolutions, is found in many fields. One closely related technique of multiscale analysis is the continuous wavelet transform. Indeed, the difference-of-Gaussian operator used in our segmentation step is a close approximation to the Mexican Hat wavelet [Antoine et al 1993]. Statisticians use convolution with Gaussian kernels of varying radii in *kernel density estimation* [Scott 1992], a non-parametric estimation technique; [Leung et al 2000] have applied scale space theory to statistical clustering using a watershed-type segmentation technique. It is worth keeping both these statistical connections in mind when later in the paper we show how the model applies to a scatterplot. A third technique that is closely related is the multiscale pyramid representation [Burt and Adelson 1983]. Originally used for image compression, it is interesting to note

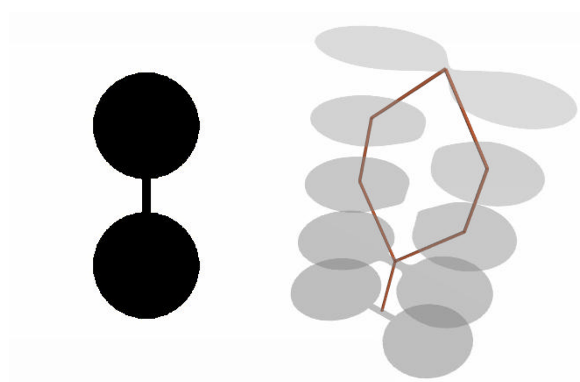

Figure 8. Image whose structure is a not tree-like. Left: original image. Right: structure of L^-.

that this structure is now used in at least one sophisticated model of visual perception [Itti 2001].

3. Results and Applications of the Model

To test our model, we built a software tool that applies the model to arbitrary input images. The tool was used to create all the images in this paper, with the exception of the hand-drawn Figures 1 and 11. As a demonstration of our model, we apply it to three case studies, and show how it can be used in the redesign of a real-life visualization.

3.1. The Software

The software tool contains the following numerical approximation of the model. We represented the image functions f_s as 2-dimensional arrays of floating-point values (one per pixel in the original image), and computed f_s for only a few discrete values of s. To perform linking, we looked at each pair of successive approximations to f_s, and connect any two segments that share a sign and which overlap. Our implementation is written in Java, and on a 700 MHz Pentium 3 PC requires up to a minute to perform a full structural analysis on a 800 x 600 pixel image at 15 scales. Once the analysis is performed, it is saved for viewing as both a series of grayscale images and as a 3D VRML file. This architecture lends itself naturally to a web-based tool, which we hope to implement in a future version.

3.2 A Simple Example: Graphs and Grid Lines

Our first example shows Gestalt cartoons of two versions of a simple graph (Figure 9). At top left is a graph with thin gridlines, at top right is a graph with overpoweringly thick ones. The segmented versions at scale s=4 are shown below. In the graph with thick gridlines the graph itself is not segmented from the background. This is an interesting indication of both the the strength of our model and one of its limitations. A human can segment the graph in the second diagram by using orientation information, which our model ignores. Nonetheless, doing so places an additional cognitive burden on the viewer, and in fact it is a standard principle of information design that grid lines should be significantly lighter than lines representing "foreground" data. Thus the model indicates, correctly, that there is a problem with the second graph. This situation—where a minor visual change has a large effect on comprehensibility—is exactly where it is useful to have a model.

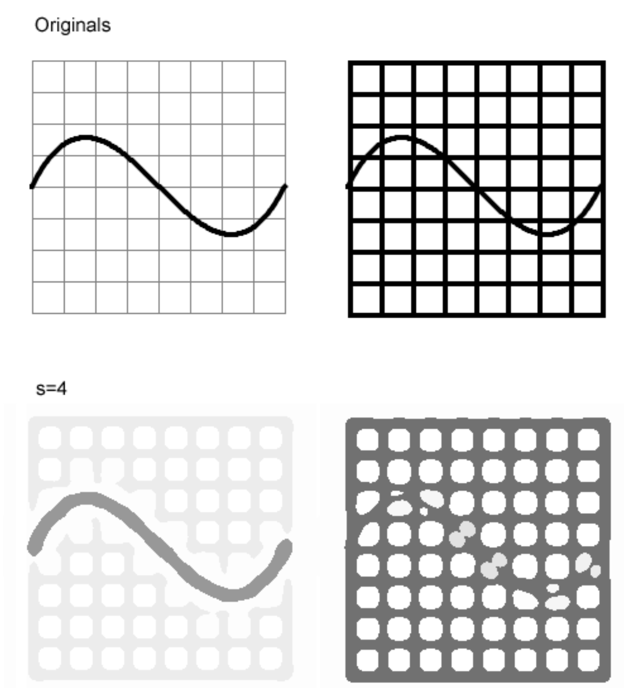

Figure 9. Gestalt cartoons showing differentiation of figure and ground in a graph. Left: thin grid lines. Right: thick grid lines.

3.3 A Famous Real-Life Example

How does the model fare on a real-life example? Figure 10 shows Gestalt cartoons for a complex scatterplot, the famous astronomical Hertzprung-Russell diagram. This scatterplot, which displays data on stars with temperature on the x-axis and absolute magnitude on the y-axis, plays a central role in scientists' conception of stellar evolution. The HR diagram at the top left of Figure 10 is reproduced directly from [Spence and Garrison 1993][2], which contains a detailed discussion of this historically significant information graphic.

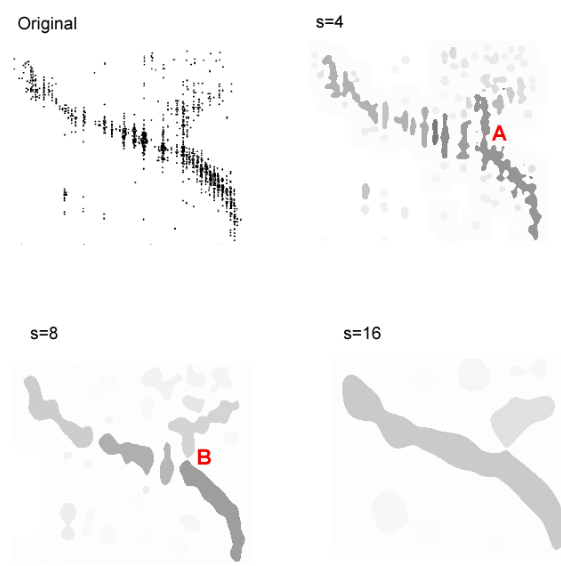

Figure 10. Gestalt Cartoons of the Hertzprung Russell diagram.

The segmentations in the Gestalt cartoons capture the intuitive experience of reading the diagram: the small-scale (s=4) view emphasizes the vertical structures, while at s=8 and s=16 the large-scale clusters stand out. The areas highlighted for s=16 correspond nicely to the standard organization given by human experts. Figure 11 shows how an astronomer structures the diagram.

The regions labeled **A** and **B** in Figure 10 show another example of how a non-tree structure can be an appropriate model. To the left and below **A** there is single large segment, reflecting the

[2] Reprinted with permission from *The American Statistician*.

small-scale structure of a combined dense vertical and diagonal cluster. But a larger scale, *s*=8, that segment has broken into two parts, at **B**, corresponding the giants and main sequence regions in Figure 11. Thus in this case our model produces a non-tree lattice structure that corresponds to perceived visual organization. This contrasts with many clustering methods and with conventional scale-space segmentation techniques, which produce trees only.

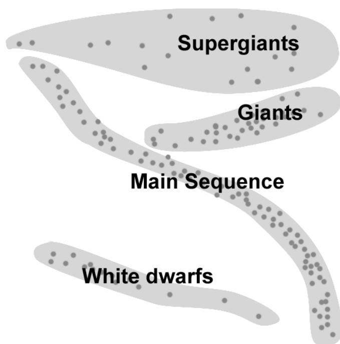

Figure 11. Human expert partitioning of HR diagram. After[Fix 1999].

3.4 A Treemap Redesign

Finally, we discuss how the model can inform the design of a visualization. We take as our example the SmartMoney Market Map [Wattenberg 1999], a treemap visualization [Shneiderman 1992] that displays data on several hundred publicly traded stocks. The first author of this paper, who led the design of the Market Map, has on many occasions heard the comment that the borders between regions are not strong enough. His intuition, however, was always that they were perfectly fine as is. Since this is exactly the kind of design issue where a perceptual model would be useful, we decided to apply our software tool. To make a comparison, we created a stylized version of the current Market Map and a redesigned version with darker and thicker borders. (See Figure 12.)

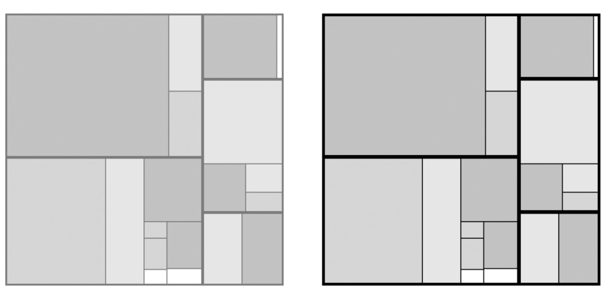

Figure 12. Left: sketch of portion of Market Map. Right: A redesign with stronger borders.

When we fed these images into our model, the results were clear. Figure 13 shows the structure derived for the current version. Note that the lattice structure is complex, confusing, and does not follow the underlying hierarchy of the data items. At point A in the diagram, for example, two items in different groups are spuriously joined. In Figure 1, the lattice structure is far simpler simpler and close to a perfect tree. This dramatic result has led to a reconsideration of the original design—exactly what we would want from a perceptual model.

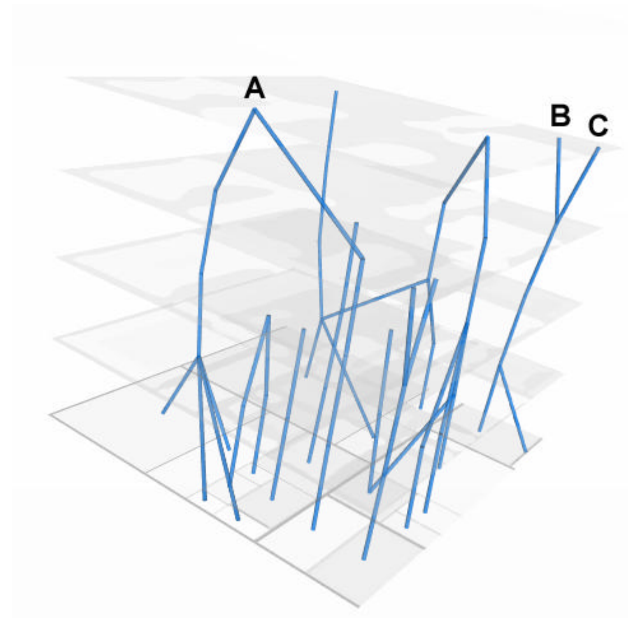

Figure 13. L^+ structure of original map design at scales up to *s*=20. Some flaws: A, two items in different groups are spuriously joined; B and C, a single group is spuriously separated.

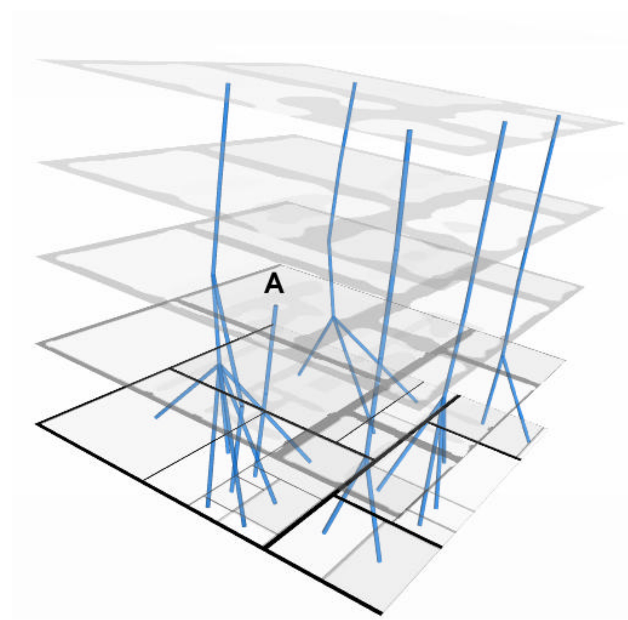

Figure 14. L^+ structure of redesigned map. Grouping is almost perfect; only flaw is an "orphan" item at A.

4. Future Directions and Extensions

The model proposed in this paper is at its core a psychological hypothesis and therefore cries out for experimental validation. There are several natural directions to investigate. One tactic would be to compare the structures generated by our model with self-reports of users' perceptions. A more pragmatic validation would be to study whether, in using the software tool described here, creators of information graphics are able to modify their designs in a way that user studies show are beneficial.

An obvious shortcoming of our model is that it applies only to grayscale images. One of the reasons to choose scale-space analysis as the basis for our method is that there is a rich body of research extending the basic idea to more general aspects of images. Theories that handle color or orientation have been proposed (for example [Perona and Malik 1990, ter Haar Romeny et al. 2001, Kalitzin et al. 1997]) and could be applied to our model. Orientation-sensitive models have the potential to address the fact that our method often confers insufficient saliency on lines and curves, which can lead to unsatisfactory analyses for graphics such as node-and-link diagrams. It may also be advantageous to use a more sophisticated segmentation method than the difference-of-gaussians edge detection employed here, since in some complicated images the simple segmentation algorithm described here can yield counterintuitive results. Finally, it would be useful to investigate ways of optimizing the numerical algorithm to run in an interactive timeframe.

5. Conclusion

We proposed a new technique for modeling multi-scale perceptual organization in information graphics. The model is based on a classical machine vision technique, scale space, with a novel method of creating links between structures at different scales. We demonstrated how a software implementation of this model captures important aspects of design aesthetics for several information graphics, and gave an example of how it may be used to give input into questions of design. We believe there is sufficient evidence of promise that it is worth extending and validating the model.

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