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Fractal dimension of landscape silhouette outlines as a predictor of landscape preference

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Abstract

The aim of this study was to explore the suggestion that fractal characteristics may play a role in aesthetic experiences by providing possible empirical evidence for connections between landscape preference and fractal properties. This approach was motivated by the knowledge that many natural forms are fractal and that, in preference research, naturalness has been found an important predictor. For reasons described in the paper, in this study we chose to focus on landscape silhouette outlines. The results indicate that there is a relationship between preference and the fractal dimension, which in turn gives rise to the hypothesis that the fractal dimension could provide part of the explanation to the well-documented connection between preference and naturalness.

Keywords: Preference; Fractal dimension; Landscape perception; Naturalness

Introduction

A considerable amount of research has sought to operationalize human aesthetic values through systematic studies of preferences and other similar aspects of experience for different types of environments. One central issue in this research has been to find the physical attributes of scenes that result in the variations in preference. A number of papers have used multivariate statistical methods to identify the underlying structure in the preferences and to make inferences based on this structure about the relevant physical attributes of the scenes. Four variables have been found to be important in preference; the degree to which a scene is natural or manmade, the extent of topographic variation, the presence or absence of water and the scale and openness of the scene with naturalness appearing to be the most significant (see, for example, Kaplan, Kaplan, & Wendt, 1972; Kaplan & Kaplan, 1982, 1989; Purcell & Lamb, 1984; Herzog, 1985, 1987; Kaplan, 1987). However, while this research has advanced knowledge in the area, the physical attributes identified are fuzzy. What for example is meant by naturalness? This has variously been associated with the presence of vegetation and how dominant it is in a scene or with the extent of human-induced change in a scene. Recent research however has shown that such conceptions of naturalness cannot account for all of the data when these concepts are made more specific and careful attention is paid to selection of stimulus material (see, for example Purcell, Lamb, Mainardi Peron, & Falchero, 1994).

Another difficult issue is how to accurately classify the large majority of our everyday environments that are in fact mixed scenes. Using an entirely qualitative interpretation based classification of scene content, it may be easy to separate extremes of urban or natural environments but it is more difficult to define the more ambiguous scenes, containing both built manmade objects and vegetation.

Fractal geometry and naturalness

Derived from the Latin 'fractus', the term fractal is used to describe fractured shapes, which possess repeating patterns when viewed at increasingly fine magnifications. This special quality of scale invariance, which shows up in many natural patterns, can be

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identified and quantified by a parameter called the fractal dimension, D. The fractal dimension has attracted considerable attention from mathematicians because its fractional quality is in sharp contrast to the integer dimensions (zero, one, two and three) of Euclidean manmade shapes such as circles and squares. The measure D of the fractal dimension is not an integer value. In fact the fractal dimension can also be defined as a measure of the extent to which a structure exceeds its base dimension to fill the next dimension. Thus, for a fractal line, D will be greater than 1 and up to 2. Similarly for a fractal surface D will have a value between 2 and 3.

The development of fractal geometry was strongly linked to issues relating to the mathematical description of forms and shapes that are found in nature such as mountain ranges and coastlines (Mandelbrot, 1983) and a considerable amount of subsequent work has demonstrated that a wide range of natural phenomena are fractal (see, for example, Barnsley, Devaney, Mandelbrot, Peitgen, Saupe, Voss, 1988; Barnsley, 1993; Gouyet, 1996). However, a most important character of the fractal dimension from the point of landscape perception is that it is a perceived dimension, i.e. related to the way the human eye views an object. For this reason it seems to be an ideal tool for judging the aesthetics of a pattern. Furthermore, because nature builds many of its patterns from fractals, the fractal dimension could be argued to identify the natural qualities, the naturalness of the pattern.

In this paper we will explore the possible connection between the fractal dimension and landscape preference using images from a wide range of scene types.

Existing empirical results on the preferred fractal dimension

There is an ongoing discussion in the general literature about fractals of how aesthetic experiences associated with natural forms could be related to their fractal characteristics. This theme has been extended to both the artificial forms that can be generated using fractal equations, to many different types of natural scenes and representations of them such as in photographs and to traditional art works (see, for example, Briggs, 1992; Bell, 1999). However, this general discussion linking fractals to aesthetic experience is not based on empirical evidence.

There are however a small number of empirical studies reporting on the relationship between the fractal dimension, D, and preference for a pattern, and here the findings are not consistent. Furthermore, the visual stimuli used have been very different, ranging from computer-generated patterns and art works to line drawings or other simplified images of natural objects such as trees and clouds. For example Pickover (1995), using computer-generated grid-like patterns, reports a most preferred D value around 1.8. Aks and Sprott (1996), also using computer-generated stimuli, reports a much lower D value, 1.3, as the most preferred. Trying to explain the differences in such results Taylor (2001) suggested that there is no universally preferred D value, but that aesthetic qualities of fractals instead depend specifically on how the fractals are generated. To test this hypothesis the fractal dimension was measured for natural fractals (scenery such as trees, mountains and clouds), mathematical fractals (computer simulations) and human fractals (sections of Jackson Pollock's paintings). The study however negated the hypothesis and found that D values in the range of 1.3–1.5 were the most preferred, irrespectively of the pattern's origin (Taylor, Newell, Spehar, & Clifford, 2001; Spehar, Clifford, Newell, & Taylor, 2003). Others have argued that the preferred D instead vary between different groups of people and may depend on personality, with a possible preference in creative persons for forms of higher dimensionality (Richards, 2001). Aks and Sprott (1996) found a similar but marginally greater preference for higher D with self-reported creative individuals. However, when objectively tested, creative individuals contrarily had a slightly greater preference for patterns with a low fractal dimension.

Procedure

The importance of the silhouette outline

We have in this study chosen to focus on the silhouette outline between sky and landscape, which is the most dominate edge in a typical landscape image. Although this means that the analysis will be limited to just one particular feature of the image, this approach was seen to have several important advantages at this initial stage of research linking fractals to environmental preferences.

- Extracting the silhouette outline can be done without subjective judgement and using standard image processing software.
- It will enable comparisons with the existing empirical findings, since the majority of them have been using drawings or similar, simpler, outline representations of natural or artificial objects and patterns.
- Studies of tall building skylines (Heath, Smith, & Lim, 2000) have found that the silhouette complexity significantly affected preference scores while façade complexity was of less importance and only influenced the evaluation of overall complexity. Thus, the study suggests that for distant views the silhouette is more important than the façade articulation.

- Building skylines have also been the focus of a recent study examining fractal contextual fit and fractal structure and the effects on preference (Stamps, 2002). The study used computer-generated images with sky and a foreground of water, against which building skylines and mountains with varying fractal dimension were presented. The result did not show any difference in preference for images where the fractal dimensions of the skyline and the mountain matched and images without this contextual fractal fit. In the second experiment, looking only at the structure of a skyline against sky and water, the respondents preferred the skylines with simple variation above those with fractal structure.
- Eye movement studies have shown that in a free viewing situation people tend to fixate semantically important areas of a scene (i.e. objects whose identity is important for understanding the scene) or visually striking areas, such as areas containing brightness changes or definite contours (Rayner & Pollatsek, 1992).
- Other studies looking at fractal dimension as a way of characterising natural scenes have successfully used a similar approach as the one in this study. For instance Keller, Crownover, and Chen (1987) used a technique where photos were taken of trees and mountain silhouettes against a sky at different distances. From these images the outlines between the sky and the tree and mountains were extracted and the fractal dimension calculated on these outlines. They found that fractal dimension, D, for trees and mountains differed considerably, with tree lines having a D value of 1.54 and 1.58 and mountain lines having a D value of 1.18. These authors also found that the value of D was insensitive to changes in scale and not dependent on how the outline was extracted. It could thus be argued that, although the outlines for the images in this study represent the landscape at only one scale, the resulting D values would be representative for the same landscape configuration at other scales, that is viewed from other distances.
- Rogowitz and Voss (1990) compared different looking objects with the same boundary D values and found similar preferences. This led them to believe that preference is based on the D value of the edges of shapes.

Stimulus material

The original images and preference data used in this study come from previous landscape preference studies (Purcell et al., 1994; Peron, Purcell, Staats, Falchero, & Lamb, 1998; Hagerhall, 2000, 2001). The first set of images consists of 60 colour slides of Swedish pastures and meadows. The images in this set was sampled to cover the range of pasture lands as defined by the existing Swedish pasture and meadows classification and the scenes contain no manmade objects, visible water, animals or people. The images were rated for preference and a number of other variables by 119 respondents randomly sampled from the general public in Sweden. Every image was shown for ten seconds for every variable and the judgement was made within this timeframe. The second set of images consists of 48 colour slides of 12 different types of outdoor scenes found in both northern Italy and Australia. Each scene type was represented by two examples from each country. A number of types of judgements including preference were made about the scenes from both countries by participants from both countries. In this study every image was shown for five seconds for every variable. The Swedish preference data used a 5 point scale and the Italian/Australian data used a 7 point preference scale. To make the preference data comparable each data set was standardized.

The advantage of using slides from previous studies is that the images are well known to the researchers and that there is a large amount of preference data already available. It was also apparent from the results of the previous research that there was a significant range in the preference judgements and that preference appeared to be associated with naturalness or the amount of human induced change. These attributes therefore make the set suitable for examining whether or not there is a relationship between the fractal dimension and preference. There is however a drawback associated with these scenes in the context of a study examining the silhouette outline. Because the images were not sampled with the analysis of fractal dimension in mind, some images could not be used in this study. For instance, images not containing any sky, such as scenes from within a forest stand, did not contain a silhouette outline and so could not be included in the analysis. Consequently, from the original sample of 108 images only 80 were used in this study.

Extracting silhouette outlines and the imaging process

The slide film had an image resolution of 40 lines per millimetre. To conserve this image resolution during the scanning process, it was necessary to scan at 4 pixels per line (Mikhail, Bethel, & McGlone, 2001, pp. 54–57, 153–155; Anders Boberg, Royal Institute of Technology, Stockholm Sweden, private communication), corresponding to 4000dpi. All of the images were scanned with the same CanoScan FS 4000 US filmscanner set at 42 bit RGB colour. As a second step the images were imported to Photoshop and the sky section of the image was selected and pasted into a new image file of the same size as the original and with a white background. From this new image file we then extracted the contour between the sky and the background, producing an

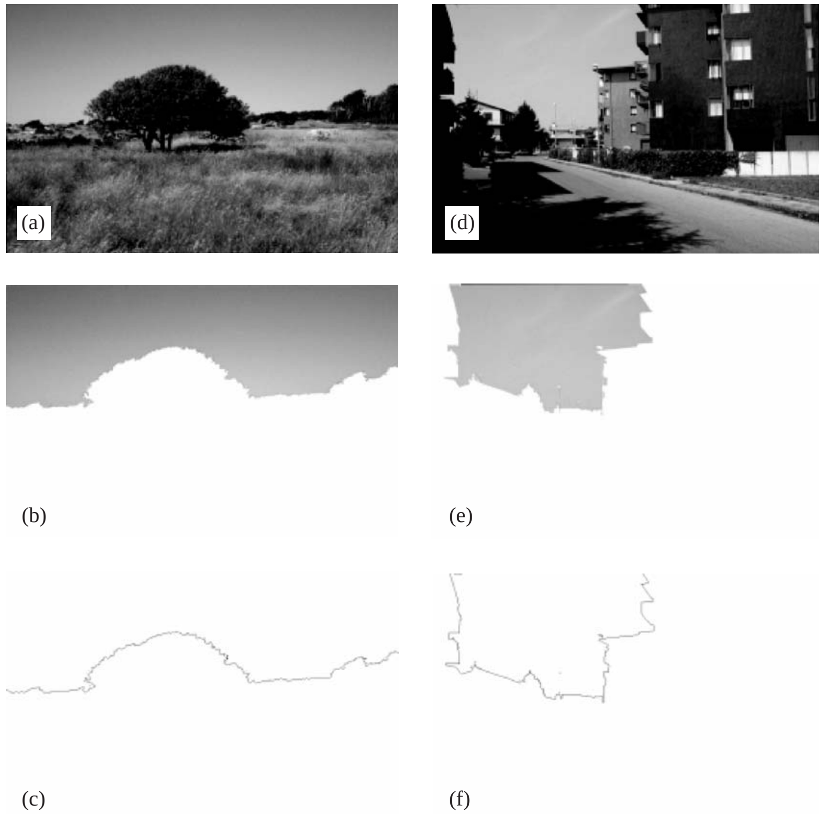

Fig. 1. The procedure for extracting the silhouette outlines from the images. The two examples show the procedure applied to a pasture landscape, images (a), (b) and, (c) and an urban landscape, images (d), (e) and (f).

image consisting of a single line tracing the contour between sky and landscape.[1] Images were saved as bitmap images with the outline in white on a black background to be compatible with the software used for the analysis of the fractal dimension. The steps in the procedure for extracting the contours are illustrated by the series of images in Fig. 1.

As can be seen from the example images in Fig. 1 the silhouette outlines in the final sample were typically made up of several different types of objects. This could be a mix of different plant species, a mix of different buildings, and in many cases also a mix of both buildings and vegetation in the same silhouette. This is an important point to keep in mind when comparing the results of this paper with other studies.

Calculating the fractal dimension

The fractal dimension, D, can be measured with a number of different methods depending on what best suits the type of data. However, the methods are similar in that they are all measuring a characteristic of the data that should be related to a length scale through a power law. To find out if the data is fractal, and to estimate the value of D, the results are plotted in log–log space. A straight line means that the data set is indeed fractal and the exponent of the slope of the line gives you the fractal dimension.

In this study we used the box counting method and the commercial software Benoit 1.3, which is specially designed for analysis of fractals. In Benoit the box count fractal dimension is defined as the exponent D in the relationship:

$$N(d) = 1/d^D,$$

where $N(d)$ is the number of boxes of linear size d necessary to cover a data set of points distributed in a two-dimensional plane.

In practise, we cover the image with a computer-generated mesh of identical squares/boxes of a size d. The number of squares $N(d)$ which contain part of the pattern is then counted.[2] This count is repeated as the size of the squares in the mesh is reduced. In this way

[1] To extract the silhouette outline, we employed the "find edges" command in Photoshop 6. To test the accuracy of this command, we applied the process to a Koch curve ($D = 1.25$) serving as a fractal test pattern and this produced a D value of 1.26. We note that the "trace contour" command produced a D value of 1.19, indicating that this second command is unsuitable for extraction of fractal lines.

[2] The grid should be overlaid in such a way that the minimum number of boxes is occupied. For this reason Benoit rotates the grid for each box size through 90°. The user can select the angular increments of rotation, which in this study was set to 15°.

the amount of the image filled by the pattern is compared at different magnifications and the scale invariance, that is characteristic of a fractal pattern, can be identified. We then plot the logarithm of $N(d)$ versus the logarithm of d. As explained earlier the plot will follow a straight line if the data set is fractal and the line will have a negative slope that equals $-D$.

The fractal dimension D was calculated in this way for all the 80 silhouette outlines and correlated to the preference data for the original images.

In addition to the scaling parameter D, an important issue in fractal analysis is the range of magnifications over which the patterns can be described by this D value. In this regard, we stress the important distinction between mathematically generated and physical fractals. Mathematical fractals span an infinite range of magnifications whilst physical fractals are only observed over a limited range. A recent survey of physical fractals (Avnir, Biham, Lidar, & Malcai, 1998) showed that a typical observation range is such that the largest pattern is only 25 times the size of the smallest pattern. In comparison, for our analysis the largest pattern is 220 times larger than the smallest pattern. This large observation range, which translates to a large range over which the data follows a straight line in the log–log plot, allows us to detect the fractal scaling behaviour with confidence. The finest feature size is limited by the slide film resolution, producing a lower cut-off for detectable fractal behaviour of 4 pixels (25 μm). The largest detectable feature size is set by the reduced statistics caused by the limited number of boxes in the mesh at large box sizes. In particular, the box counting becomes unreliable for meshes featuring less than a 6×6 array of boxes. This condition sets the upper cut-off for fractal detection at 882 pixels (5.5 mm). The fractal observation range, residing between these lower and upper cut-offs, features typically 20 data points, and the fitting procedure produced D values with a standard deviation, S.D., ranging from 0.003 to 0.16. Within this range 61% of the D values had a S.D. lower than 0.03 and 75% a S.D. lower than 0.05. Only 5% of the S.D. values were above 0.10.

Results

An initial plot of the mean preference ratings and the D values for the 80 silhouette outlines, Fig. 2, shows quite a lot of scatter and the correlation between preference and the fractal dimension is not significant, $p<0.15$, $r^2 = 0.26$. Especially, there seems to be a group of images with high preference and low D (the upper left-hand corner of the figure) that stand out somewhat from the rest of the data.

A closer examination of these images revealed that many of the images with low D value and high preference were images with visible water or dominant hilly topography. Examples of such images can be seen in Fig. 3. As mentioned in the introduction previous landscape preference studies have pointed out that visible water and hills have a particular impact on people's perception and preference (see, for example, Kaplan & Kaplan, 1982; Purcell & Lamb, 1984). It could therefore be argued that the silhouette outline in an image with dominant water or hills would attract less of the respondents focus when evaluating such scenes. The preference rating for such images would consequently be dominated by the content of the scene and have less to do with the shape of the silhouette line.

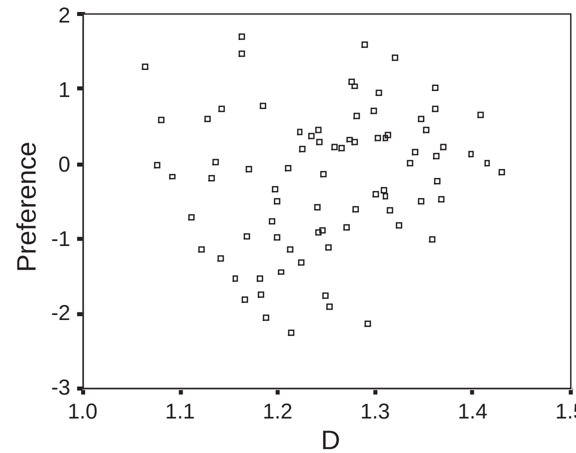

Fig. 2. Plot of the mean preference ratings for the images and the D values for the silhouette outlines, for all the 80 scenes.

For this reason we found it interesting to do a second analysis in which all scenes containing any visible water or hills were omitted. The exclusion of scenes was made using visual inspection and based on judgement by the researchers with the exclusion rule being that if any water or hills was at all visible the scene was excluded. As can be seen in Fig. 4 the excluded images, represented by filled black data points in the figure, are not restricted to a particular part of the plot. Excluded images are found over the whole range of preference and D.

The exclusion of images resulted in a sample with 52 silhouette outlines. For this sample linear regression shows a significant correlation between preference and D. The standard deviation of the calculated D values ranged from 0.005 to 0.11 with 67% of the D values having a S.D. lower than 0.03 and 79% an S.D. lower than 0.05. Only 4% of the D values had a S.D. above 0.10. The plot of preference and the D values for this set of scenes are presented in Fig. 5. As can be seen in the accompanying ANOVA, Table 1, there is a significant correlation between the mean preference for an image and the fractal dimension of the extracted silhouette outline.[3] However, it should be noted that the model fit is quite low, r^2 0.34.

[3]The reader should note that this study used data from previous studies and therefore the data used did not constitute an independent sample.

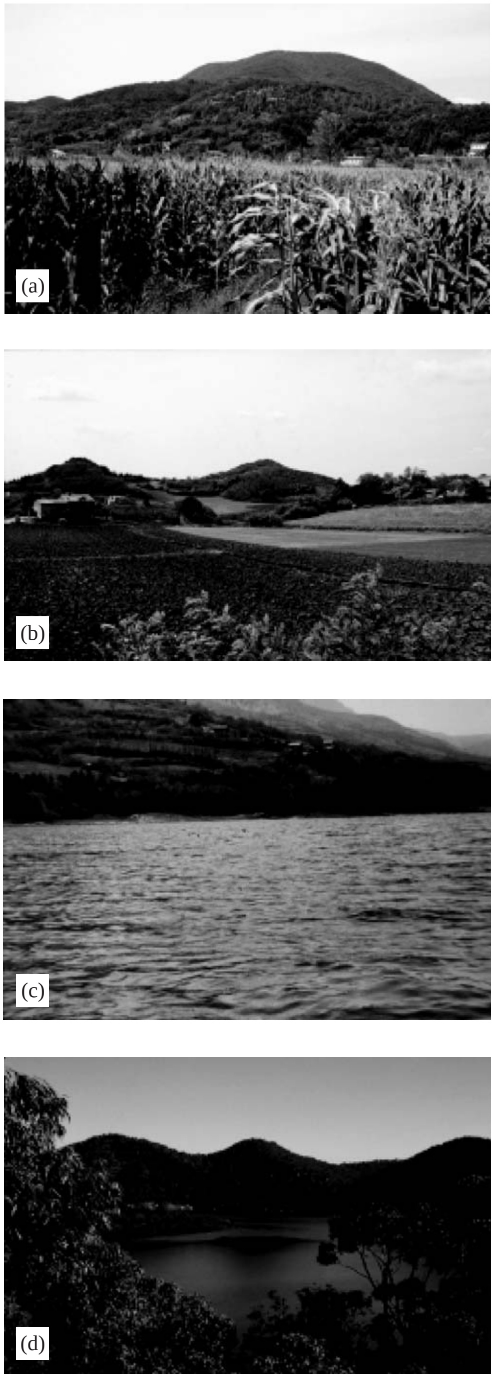

Fig. 3. Examples of excluded images with visible water or dominant hilly topography.

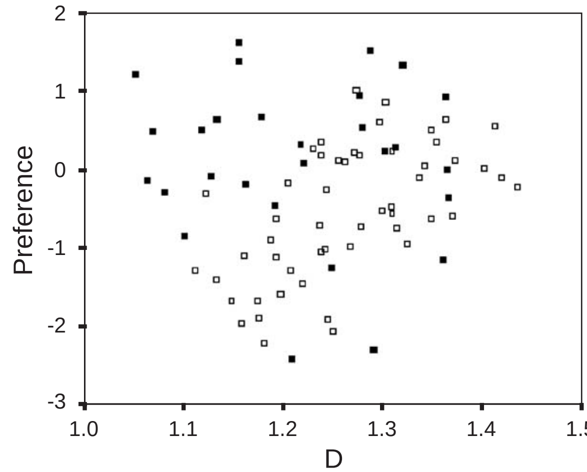

Fig. 4. Plot of the mean preference ratings for the images and the *D* values for the silhouette outlines, for all the 80 scenes. Filled black data points represent scenes containing visible water or dominant hilly topography.

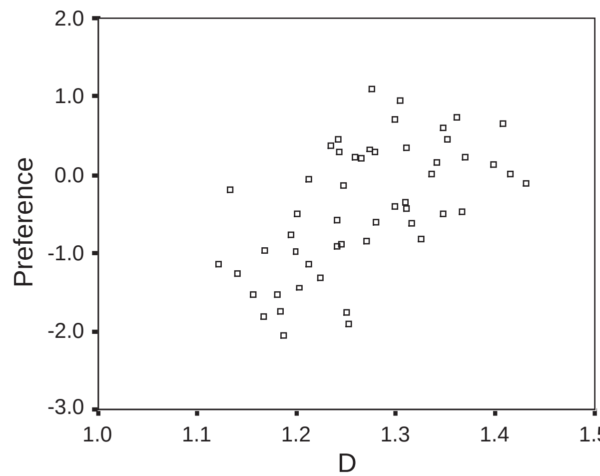

Fig. 5. Plot of the mean preference ratings for the images and the *D* values for the silhouette outlines, for the 52 scenes without visible water or dominant hilly topography.

Table 1
Linear regression for the mean preference for an image and the fractal dimension of the extracted silhouette outline

ANOVA[a] Model		Sum of squares	df	Mean square	*F*	Sig.
1	Regression	11.573	1	11.573	25.692	0.000[b]
	Residual	22.522	50	0.450		
	Total	34.095	51			

Images with visible water or dominant hilly topography excluded.
[a] Dependent variable: preference.
[b] Predictors: (Constant), *D*.

Discussion

The ubiquity of fractals in the natural environment has motivated a number of theories concerning the relationship between the pattern's fractal character and the corresponding perceived visual qualities. The ability of observers to discriminate between fractal images based on their *D* value has been shown to be maximal for fractal images with *D* values corresponding to those of natural scenes (Knill, Field, & Kersten, 1990; Geake & Landini, 1997), triggering discussions as to whether the sensitivity of the visual system is adapted to the fractal statistics of natural environments (Knill et al., 1990; Gilden, Schmuckler, & Clayton, 1993). Observers who displayed a superior ability to distinguish between different D values were also found to excel in cognitive tasks involving 'simultaneous synthesis' (the ability to combine current perceptual information with information from long-term memory), with the authors speculating that natural fractal imagery resides in the long-term memory (Geake & Landini, 1997). Furthermore, Aks and Sprott (1996) noted that the aesthetically preferred D value of 1.3 revealed in their studies corresponds to fractals frequently found in natural environments (for example, clouds) and suggested that people's preference is actually *set* at 1.3 through continuous visual exposure to nature's patterns. Others have discussed fractal perception in terms of evolution, for example Richard Voss notes: "The human perception system has evolved over millions of years in a natural fractal environment. Only recently, by evolutionary time scales have we found ourselves in a primarily Euclidean environment of straight lines and few spatial scales" (Rogowitz & Voss, 1990). Indeed, it is interesting to consider our results within the context of previously proposed evolutionary theory of aesthetics, in which a scene's attraction is related to survival instinct (Appleton, 1975; Ulrich, 1993; Wise & Leigh Hazzard, 2000; Barrow, 2003). It has been speculated that observers may have preferred images with low D values because the low D image mimics African savannah scenery (Wise & Leigh Hazzard, 2000). Our ancestors spent the bulk of their evolutionary history in this landscape, and its low visual complexity facilitates detection of predators (Barrow, 2003). Observers may have judged the high D images as too intricate and complicated, where detecting predators from the surrounding vegetation would be difficult. Such theories add to the topic of the degree to which our aesthetic judgments are based on evolutionary (Appleton, 1975; Balling & Falk, 1982; Ulrich, 1983; Orians, 1986; Kaplan & Kaplan, 1989; Orians & Heerwagen, 1992; Ulrich, 1993; Barrow, 2003) or biological factors (Zeki, 1999) rather than personal subjective preference.

In Fig. 5 it is apparent that there is a rise in preference with increased D up to a point around $D = 1.3$ where the data seems to peak. This is consistent with Aks and Sprott (1996) who found the most preferred D to be 1.3. It is also in part consistent with Taylor (2001) who found D values in the range of 1.3–1.5 the most preferred. However, in our study, the plot Fig. 5 seems to indicate that there could be a drop in preference as D increases above 1.3. Unfortunately, the lack of scenes with higher D makes it impossible to pursue this further here.

A possible reason for the absence of scenes with high D and low preference and the limited range of D values found in this analysis could lie in the constraints placed on the types of scenes that could be included in this analysis. Because, for the reasons outlined previously, we chose to look first for a relationship between the fractal dimension and preference using the silhouette outline, we excluded sets of examples where no such line was present. Some of the excluded, more enclosed scenes, such as views from within a forest, were among the less preferred in the original studies and could also be assumed to have a higher D.

It is also appropriate at this point to comment on the study mentioned earlier by Keller et al. (1987) in which D values around 1.5 were reported for silhouette outlines comprised of trees. None of our images with only vegetation have equally high D values. A possible explanation for the difference could be different mixes of plants in the silhouettes from the two studies. It is known, from studies using close up photographs of single species, that different species have different D values (Morse, Lawton, Dodson, & Williamson, 1985). It is thus not unlikely that particular plants could make a difference in the D value of a mixed vegetation outline, also when viewed from a distance. However, we do not have enough detailed information about the species in our images, or the tree images in the Keller et al. paper, to investigate this further at this point.

Another factor that could contribute to the difference in results is that the two studies used different methods for the calculation of D. Absolutely accurate comparison of dimensions of different data sets would require that the same method be used for the calculations.

Conclusion

The significant relationship between preference and the fractal dimension D found in this analysis indicates that this particular geometry may be part of the basis for preference. The found connection also gives rise to the hypothesis that the fractal dimension could provide an explanation to the well-documented connection between preference and naturalness.

The conclusion that preference is significantly related to the fractal dimension must however be treated with considerable caution at this stage. An approach based on extraction of contours has limitations, especially in that the image analysed is a strong simplification of the original image. Furthermore, the extraction of contours is a process that in many cases would involve some subjective judgements. It would therefore be of great interest to explore fractal analysis techniques that could be applied to a greyscale image.

There are several interesting such techniques being applied in other fields of research. Some examples are research using the fractal dimension for texture discrimination (Pentland, 1984; Keller, Chen, & Crownover, 1989) and vision research looking at luminance patterns in natural scenes (Field & Brady, 1997). We believe these analysis techniques could be very useful in a further exploration of the link between landscape preference and fractal properties. We are therefore embarking on projects in this direction with novel constellations of researchers from the relevant disciplines. It can be noted that the fractal dimension of a texture has been found to correlate strongly with the roughness perceived by observers (Pentland, 1984; Jang & Rajala, 1990). This adds to the view of this approach as a relevant and promising way of linking the fractal dimension of textured greyscale images to the perceived preference.

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