Measuring Naturalness and Complexity Using the Fractal Dimensions of Landscape Photographs

Agnès Patuano

The University of Edinburgh, Scotland/UK · apatuano@exseed.ed.ac.uk

Abstract: The fractal analysis of images is a common technique to study natural processes. Its application to landscape photographs, however, requires pre-processing which can produce widely different results. Using two categories of landscape scenes with different levels of vegetation, five types of image segmentation were compared and the resulting structures analysed with the box-counting method. The fractal dimensions estimated were compared and found to characterize either the naturalness or the complexity of the landscape scenes. This demonstrates the potential of fractal analysis for landscape perception studies, and offers a set of reliable methods to estimate the fractal dimensions of landscape photographs.

Keywords: Fractal dimension, image segmentation, landscape photographs

1 Introduction

Studies on the perception of natural landscapes have demonstrated over the years that specific qualities of an environment, such as its complexity and naturalness, are positively associated with preference (KAPLAN & KAPLAN 1989). However, the lack of formal definition of such terms makes their assessment difficult. Typically, naturalness is often linked to the presence of vegetation, with high vegetation such as forests often perceived as more natural than meadows, without it correlating with actual measures of biodiversity or other ecological indicators (LAMB & PURCELL 1990). Similarly, complexity has been linked to visual variety or entropy, but a valid measurement of the concept is still being investigated. Recently, FORSYTHE et al. (2011) showed that the size of digital images compressed in a lossless format was a good approximation of their perceived complexity.

With the development of new technology, fractal analysis has been sparking interest as the method most able to quantify a landscape's elements and qualities based on the statistical structure of its visual representations. This method is already widely used in Ecology and Medical Imaging, as the fractal dimension of images has been found to be a good surrogate for the fractal dimension of the object represented (PENTLAND 1984). Using this approach, patterns can be characterized by their fractal dimension, noted D, a statistical quantification of their roughness or complexity (MANDELBROT 1982).

Most notably, COOPER & OSKROCHI (2008) showed that the extracted edges of street photographs could successfully discriminate between levels of perceived complexity. In a follow-up study, urban scenes with higher levels of vegetation were found to exhibit higher fractal dimensions than others with higher amounts of visibly built features (COOPER et al. 2013). Typically, studies have found that the perceived naturalness of outdoor scenes increased with their fractal dimension (KELLER et al. 1987) Images with mid-range fractal dimensions were also found to be optimum in inducing the responses typically associated with landscape scenes showing large amounts of naturalness or complexity (TAYLOR et al. 2001).

Journal of Digital Landscape Architecture, 3-2018, pp. 328-335. © Wichmann Verlag, VDE VERLAG GMBH · Berlin · Offenbach. ISBN 978-3-87907-642-0, ISSN 2367-4253, e-ISSN 2511-624X, doi:10.14627/537642035.

This paper succinctly presents the results obtained in the first half of a study exploring the use of fractal analysis of landscape photographs as a predictive tool for landscape preference. However, the application of fractal analysis to landscape images is a relatively new area of research and is still in need of a thorough investigation. Therefore, the first questions this study had to address were: what is the fractal dimension of a landscape? How can it be measured? And how can it be interpreted?

1.1 The Box Counting Method

At the time of writing, most studies on the perception of fractal patterns had been carried out on computer-generated images which exhibit specific fractal behaviours different from physical objects. Those who used real data often applied a simple method, called the Box-Counting Method (BCM), to estimate the D value of their data (COOPER et al. 2013, COOPER & OSKROCHI 2008, HAGERHALL et al. 2004, TAYLOR et al. 2001). The BCM consists of overlaying a series of grids on the image, and counting the number of boxes or tiles that contain a piece of pattern. However, it has many theoretical and practical limitations in its application to digital images, as it is said to be particularly sensitive to changes in its parameters, such as the software used, the size of the grid and its increment of rotation (OSTWALD 2013).

Furthermore, as the BCM can only be applied to binary images, where a pattern or object is distinct from the background, it is necessary to segment the images in pre-processing of the analysis. This step becomes critical in the case of landscape photographs which can record scenes in which adjacent elements are not always perceptibly different or distinct from each other. In order to establish the replicability and validity of fractal analysis by BCM as a tool for landscape analysis, five different types of image segmentations were applied to a set of landscape images (see Figure 2).

1.2 Experimental Picture Set

The set consisted of 58 pictures from the Forestry Commission database equally divided between two types of landscapes: forests and meadows. The photographs contained in the database are taken by individuals and professionals alike, across properties managed by the institution and, as such, display a wide range of quality, lighting conditions, focal length, etc. The images were mainly chosen for their content of entirely natural landscapes from the United Kingdom, showing no or little sign of manmade artefact, and no water feature as those typically affect preference ratings (HAGERHALL et al. 2004). Each chosen image was calibrated to a resolution of 300 ppi/8 bit and to a size of 900 × 598 pixels, encoded in .bmp format with lossless compression.

Forests scenes were characterised by the height of their vegetation such as trees and high shrubs which would often reduce the visible portion of sky. Comparatively, the images of Meadows typically displayed much larger areas of visible sky, with a low height of vegetation. Some of them were of cultivated vegetation, while others were not. Similarly, some meadows were bordered by trees while others were not (see Figure 1). The validity of the BCM was assessed through its expected ability to discriminate between two types of landscapes. In order to study the consistency of fractal dimension across a single landscape, ten pairs or trios of images were also chosen from the same location and represent the landscape photographed from different viewpoints (see Figure 3).

Fig. 1: Example of photographs in the experimental set. Two forests and two meadows.

1.3 Image Segmentation and Fractal Analysis

Prior to the analysis, three softwares (BENOIT™, Fractalyse and HarFA 5.5)[1] were calibrated using Euclidean test images such as straight lines or fractals of known dimensions. The results showed some fluctuations when the parameters of application of the grid were changed or with images of lesser resolutions. Nevertheless, these variations remained within the software's error margins which were all under 5 %. Fractalyse gave the worst performance with an average error margin of 36 % and was removed from the rest of the experiment.

HarFA offers different options for the segmentation of images and for the analysis of complex greyscale photographs, such as its *Fractal range analysis* tool, which estimates the fractal dimension at every intensity levels displayed by the pixels of the original image. The information thus collected takes the shape of a *fractal spectrum*, where the fractal dimension is presented as a function of thresholding conditions.

Three types of segmentation were applied to the landscape photographs: the extracted edges, the silhouette outline, and the greyscale analysis reduced to the thresholding conditions at three points of the fractal spectrum: the minimum, maximum and average fractal dimensions (see Figure 2). The detail of the protocols followed for each segmentation can be found in Table 1. A fractal analysis was then conducted on each structure using the two remaining softwares.

Following the recommendation of COOPER & OSKROCHI (2008) and OSTWALD (2013), the images were all analysed between 0.23l and 0.03l, where l is the height of the image. In the case of this set, the analysis was carried out between 149 and 17 pixels. In other words, the largest grid had boxes of length 149 × 149 pixels, and the smallest 17 × 17 pixels. The placement of the grid was also started at the top left-hand corner, although that parameter was found to have a limited influence on the results. In total, 10 values of D were estimated for each photograph.

[1] HarFA (Harmonic and Fractal Image Analysis) is a software compiled by the Brno University of Technology. The Fractalyse software was developed by the research team "Mobility, city and transport" of the research centre TheMA. Both can be freely downloaded online.

Table 1: Protocol followed for the image segmentations applied as pre-processing of the BCM

Extracted Edges	Silhouette Outline	Greyscale	
		For HarFA	For BENOIT™
Removing the sky portion of the image: 1. Open file with Photoshop 2. Switch to *Greyscale mode* 3. To remove the sky, use the *Selection by Colour* range with the parameters: (a) 1-20 fuzziness (b) No feather 4. Finalise the image by manually removing any leftover pixels in the sky area. 5. Save as .bmp file.			
6. Use the *Find Edges filter* (a 3x3 Sobel filter) 7. Threshold the image at intensity level 128 8. Finalize the image and manually clean up any leftover pixels from other parts of the image. 9. Save as.bmp file. That image can be processed by HarFA Invert and save as another .bmp file to analyse with BENOIT™.	6. Copy and paste the sky area previously selected (3) into a new image with the same dimensions and resolution as original 7. Trace the outline of that image using the *Find Edges filter*. (Alternatively, if the sky is too bright, use *Stroke* to trace a 1px contour of the selection). Merge layers 9. Threshold the image at intensity level 128 (Alternatively, if the image is too bright, the level can be raised so that the outline is clearly visible). 10. Follow step 8 and 9 from the extracted edges protocol.	6. Open file with HarFA 7. Open fractal analysis tool 8. Select darkest intensity visible to start thresholding 9. Launch analysis tool 10. Stop when landscape is entirely white. 11. Visualize fractal spectrum. Show D(BW) 13. Graphically read higher and lower D and record corresponding thresholding values.	6. Use *Threshold adjustment*: input the intensity values read on the fractal spectrum for the minimum, maximum and average value of D, producing 3 different files. 7. Because HarFA carries out a BW analysis which only takes into account the pattern's outline, the images need to be simplified, using the *Find Edges filter*. 8. Use the Invert adjustment tool so the images appear white on black. 9. Save as .bmp file.

2 Results of the Fractal Analysis

2.1 Comparisons of Results by Software and Segmentation Types

Non-parametric correlation tests were applied to all individual variables and the Kendall's tau coefficient observed for correlation between the D values obtained by software and segmentation type.

The values least correlated between software were the average fractal dimension values estimated from greyscale, with $\tau = .526$, possibly because of the heavy manipulations required for that analysis (see Table 1). Comparatively, the values of D of the extracted edges and the ones of the silhouette outline were strongly consistent across software with $\tau = .925$ and $\tau = .811$, respectively. All correlations were strongly significant ($p < .0001$). Therefore, the values of D could be safely averaged between the two software packages for the rest of the analysis.

There was a strong correlation between the fractal dimensions values obtained from silhouette outlines and the minimum fractal dimensions calculated from greyscale, $\tau = .609$, $p < .01$. This could be due to the fact that the thresholded images corresponding to the minimum fractal dimension were often reduced to the single line of their silhouette (see image (a) and (c) in Figure 2).

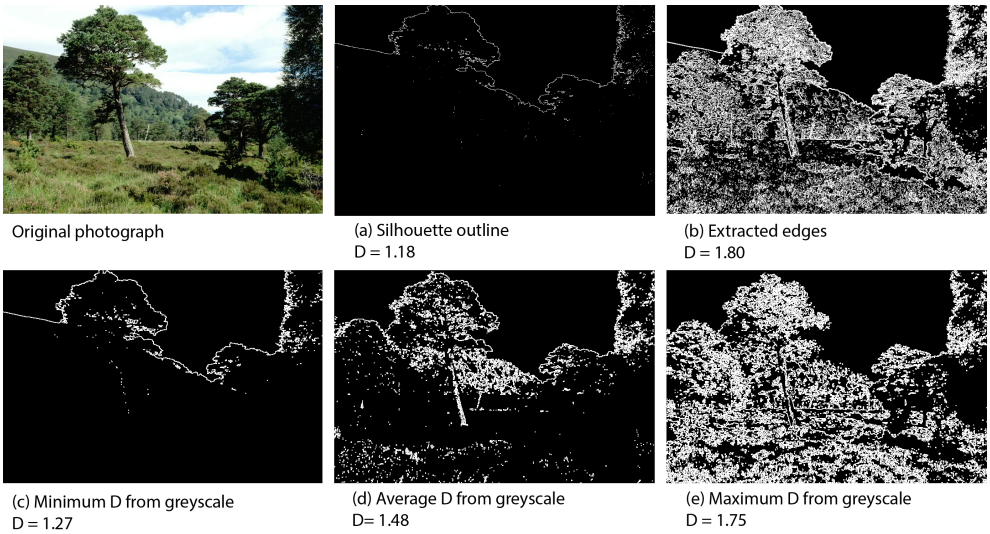

Fig. 2: The different types of segmentation applied to the original photograph as pre-processing for the fractal analysis. The fractal dimensions indicated here are the average value estimated by the two softwares BENOIT™ and HArFA.

However, there was no significant correlation between the results obtained with the silhouette outline method and those calculated from extracted edges, or even the average or maximum fractal dimension calculated from greyscale. Overall, the three greyscale variables were not as correlated as expected. Although both minimum and maximum fractal dimension were significantly related ($\tau = -.247$, $p < .01$), the average was not. Instead, the average fractal dimension calculated from greyscale was strongly related to the fractal dimension obtained using the extracted edges ($\tau = .324$, $p < .01$), which was also weakly correlated to the maximum fractal dimension obtained from greyscale ($\tau = .202$, $p < .05$).

2.2 Comparison of Results by Landscape Type

In order to assess the validity of the method, a Mann-Whitney U test was used on the averaged values between software, grouped by image type. The values of fractal dimension estimated from the silhouette outline were found to be significantly greater for Forests (M = 1.34, SD = .11) than for Meadows (M = 1.12, SD = .089), U = 30.00, $p < .0001$. This difference was also visible in the minimum fractal dimensions estimated from greyscale U = 51.00, $p < .0001$.The fractal dimensions measured from the images produced by other methods of segmentation did not show any significant differences between the two landscape types.

2.3 Principal Components Analysis

A principal component analysis was carried out with Varimax rotation using only the variables with the strongest correlations to each other which excluded the maximum D estimated from greyscale (Bartlett's, $p < .0001$).

An initial analysis was run to determine the explanatory power of the components underlying the data. Two components fulfilled the criterion of having eigenvalues above 1, and in combination explained 79.85 % of the variance in the values of D. The fractal dimensions estimated either from the landscapes silhouette outlines or the lowest threshold of the greyscale spectrum had factor loadings on the first component of, respectively, .891 and .912. Since the categorical variable coding for landscape type had a factor loading of .865 on that same component, it seems that the latent variable measured here is linked to the type of landscape, either described through vegetation levels, density of vertical elements or naturalness.

The other variables, the fractal dimension of the extracted edges and the average fractal dimension estimated from the greyscale spectrum, had factor loading of .699 and .756, respectively, on the second component. In order to determinate what that latent variable measured, a secondary analysis was carried out using the size of the image files compressed in a lossless format (.gif), following the recommendations of FORSYTHE et al. (2011). The size of images was found to be significantly correlated to the values of D estimated from the extracted edges and the average values of D measured from greyscale, which confirms that these two variables measured something akin to complexity.

2.4 Landscape Viewpoints

There was no significant correlation between the pairs of images taken from different viewpoints of the same landscapes. Some exhibited very different outlines but similar edges, whereas some had the opposite relationship (Figure 4). In most cases, the difference in the fractal dimension of the outlines was caused by the presence of trees in one of the images.

The difference between the fractal dimensions of the extracted edges was subtler but mostly linked to one photograph being more contrasted than the other.

This illustrates both the effect of vertical elements for the D value of the silhouette outline, and the importance of strong contrast levels for the edge detection Sobel filter used in the extracted edges segmentation.

Fig. 4:
Two pairs of photographs representing the same landscape, taken from different viewpoints. The first pair (top row) shares the fractal dimension of their extracted edges but not the one of their silhouette outlines, The second pair (bottom row) exhibits the opposite relationship.

3 Discussion and Conclusion

The results obtained here show how critical the type of image segmentation applied to landscape photographs is for the replicability and validity of their fractal analysis. Although most methods will yield higher D values for forest images than for meadows, the silhouette outline is the only method that can significantly discriminate between the two landscape types. This segmentation is also relatively easy to implement compared to the greyscale thresholding spectrum and a full horizon line is not necessary, as some images in the experimental set had portions of sky smaller than a quarter of their length and width and could still be included in the final analysis. However, one limitation encompasses all segmentation techniques: the contrast between landscape and sky. Indeed the sky must display lighter and bluer tones than the vegetation and landforms for its contour to be efficiently extracted (Table 1 presents a detailed protocol including alternative steps for less contrasted images).

The differences between the D values of forest and meadow images support previous claims that link D with the presence of vertical elements, visual variety and high levels of vegetation (COOPER 2013, COOPER & OSKROCHI 2008, KELLER et al. 1987). However, the present study demonstrates that these can also be associated with the contrast levels of an image, depending on which segmentation technique is used in pre-processing of the fractal analysis. Therefore, the method of segmentation has a stronger influence on the values of D estimated than the subject of the photograph itself.

Similarly, two photographs of the same landscape can exhibit different properties depending on what the camera captured. Factors such as viewpoints, but also light levels, time of day or the quality of the camera, will influence the data from which D will be estimated. Therefore, the fractal dimension of a landscape can only be defined as the fractal dimension of a specific representation of that landscape.

Consequently, the labels of naturalness and complexity used in the present paper should be used with caution. Indeed, the naturalness illustrated here rests on the presence of trees and vertical elements, which does not encompass such natural settings as deserts or coastal environments. Similarly, previous studies which associated higher fractal dimensions to naturalness and complexity, such as COOPER & OSKROCHI (2008) and COOPER et al. (2013) were carried out within urban contexts where the presence of vegetation is most likely to stand out. It would certainly be interesting to see if fractal geometry could be used to quantify objective

indicators of natural health such as biodiversity, or if its usefulness is limited to perceptible qualities. With a more extensive picture set covering a wider range of landscape types and landscape elements, the visual interpretation of D could be refined.

Regardless of the interpretation, it is important to note that Mandelbrot himself warned that two objects could share the same fractal dimension yet look nothing alike (MANDELBROT 1982). As an example, images of urban environments were included in the pilot part of this study and some were found to exhibit the same mid-range fractal dimensions typically associated with naturalness (TAYLOR et al. 2001). It is therefore impossible to rely on the fractal dimension alone to visually describe a pattern. Instead, one should look to other measurements described within fractal geometry, such as lacunarity or randomness.

Although further work is needed to refine the reliability of this new method, the contribution of fractal geometry to landscape studies, particularly those interested in the perceptual mechanisms behind preference remains promising. Indeed, in the second half of the study, two distinct measures of the fractal dimension of landscape photographs presented here were found to significantly correlate with preference ratings.

References

CHEUNG, K. & WELLS, N. (2004), The Natural Environment & Human Well-Being: Insights From Fractal Composition Analysis. HarFA e-journal, 76-82.

COOPER, J., SU, M.-L. & OSKROCHI, R. (2013), The Influence Of Fractal Dimension And Vegetation on the Percpetions of Streetscape Quality in Taipei. Environment and Planning B: Planning and Design, 40 (1), 43-62.

COOPER, J. & OSKROCHI, R. (2008), Fractal Analysis of Street Vistas: A Potential Tool For Assessing Levels of Visual Variety in Everyday Street Scenes. Environment and Planning B: Planning and Design, 35 (2), 349-363.

FORSYTHE, A. et al. (2011), Predicting beauty: Fractal Dimension and Visual Complexity in Art. British Journal of Psychology, 102 (1), 49-70.

HAGERHALL, C. M., PURCELL, T. & TAYLOR, R. P. (2004), Fractal Dimension of Landscape Silhouette Outlines as a Predictor of Landscape Preference. Journal of Environmental Psychology, 24 (2), 247-255.

KAPLAN, R. & KAPLAN, S. (1989), The experience of nature: A psychological perspective. Cambridge University Press.

KELLER, J. M., CROWNOVER, R. M. & CHEN, R. Y. (1987), Characteristics of Natural Scenes Related to the Fractal Dimension. IEEE Transactions on Pattern Analysis and Machine Intelligence, PAMI-9 (5), 621-627.

LAMB, R. & PURCELL, A. (1990), Perception of Naturalness in Landscape and its Relationship to Vegetation Structure. Landscape and Urban Planning, 19, 333-352.

MANDELBROT, B. B. (1982), The Fractal Geometry of Nature 3d. FREEMAN, W. H. (Ed.).

OSTWALD, M. J. (2013), The Fractal Analysis of Architecture: Calibrating the Box-Counting Method Using Scaling Coefficient and Grid Disposition Variables. In: Environment and Planning B: Planning and Design, 40, 644-663.

PENTLAND, A. P. (1984), Fractal-Based Description of Natural Scenes. IEEE Transactions on Pattern Analysis and Machine Intelligence, PAMI-6 (6), 661-674.

TAYLOR, R., NEWELL, B., SPEHAR, B. & CLFFORD, C. (2001), Fractals: A Resonance between Art and Nature. Mathematics and Culture II, 53-63.