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Predicting beauty: Fractal dimension and visual complexity in art

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Visual complexity has been known to be a significant predictor of preference for artistic works for some time. The first study reported here examines the extent to which perceived visual complexity in art can be successfully predicted using automated measures of complexity. Contrary to previous findings the most successful predictor of visual complexity was Gif compression. The second study examined the extent to which fractal dimension could account for judgments of perceived beauty. The fractal dimension measure accounts for more of the variance in judgments of perceived beauty in visual art than measures of visual complexity alone, particularly for abstract and natural images. Results also suggest that when colour is removed from an artistic image observers are unable to make meaningful judgments as to its beauty.

Measuring visual complexity

Finding a measure for the mathematical and psychological complexity of an image has been of interest for some time (Attneave & Arnoult, 1956; Chipman, 1977; Garcia, Badre, & Stasko, 1994; Hochberg & Brooks, 1960). The measures that have been developed tend to be based on a counting system whereby elements (lines and angles) and the regularity, irregularity, and heterogeneity of those elements additively contribute to a mathematical calculation of visual complexity (Birkhoff, 1933; Eysenck, 1941, 1968; Eysenck & Castle, 1970; Jacobsen & Höfel, 2003).

Capturing a definitive measure is not straightforward. Some of the theory-based metrics of visual complexity have progressed conceptual understanding but translating theory into practice has been challenging for those who design, for example, visual display interfaces. The degree of detailed measurement involved in the identification, calculation, and documentation of primitive image components is time consuming and

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it is often difficult to replicate the results (Forsythe, Mulhern, & Sawey, 2008; Forsythe, Sheehy, & Sawey, 2003). Rump (1968) has gone as far as to suggest that the general concept of visual complexity is meaningless; the way a stimulus is perceived is more important than the number of elements (Hogeboom & Van Leeuwen, 1997; Strother & Kubovy, 2003). However, visual complexity and the development of a reliable measure remains of interest; as argued by Hochberg (1968) without an accurate measure of visual complexity, how can one be certain how simple or complex and image actually is?

Norm measures (see, for example, Proctor and Vu (1999) for an index of norms and ratings published in the Psychonomic Society journals) tend to be the most straightforward and popular way by which to determine the extent to which most people perceive a picture as complex or simple. Measures such as these are collected by surveying large numbers of people by asking them to make judgments about various characteristics such as complexity, familiarity, and concreteness. However, some of these measures are not completely reliable. Forsythe *et al.* (2008) found that unfamiliar visual stimuli tend to be rated as more complex than they physically are. One explanation for this interaction is that an upper complexity limit is fixed early in visual processing (Chipman, 1977); elementary components are processed, but there comes a point when the structural aspects of stimuli (symmetry, rotation, and repetition) reduce the perceived complexity. Forsythe *et al.* (2008) suggest that familiarity possibly interacts at a third level. As the elementary components become organized they are perceived as familiar objects. Top-down processing enables sensemaking and the visual system is able to overlook small details reducing perceived complexity.

Algorithms seem to offer the most promising development in the measurement of visual complexity. Lempel and Ziv (1976) developed the earliest model. Their algorithm for complexity was based on the smallest computer program required to store/produce an image and it is this algorithm that is the basis for the compression techniques we use today. Recent developments in the analysis of visual complexity have applied such algorithms in the study of visual complexity (Donderi, 2006b; Forsythe *et al.*, 2008).

A compressed image consists of a string of numbers that represent the organization of that picture. This string is a measure of information content (Donderi, 2006b). When the image contains few elements or is more homogeneous in design, there are few message alternatives and as such the file string contains mostly numbers to be repeated. A more complex picture will have more image elements and these elements will be less predictable: the file string will be longer and contain an increasing number of alternatives.

To understand and measure visual complexity, it is vitally important to develop a measure that is theoretically informed and can account for some of the processes involved in the perception of complexity. Grounded in information theory (Shannon & Weaver, 1949), compression techniques are promising because they are able not only to account for the lines and elements in an image, but they are also able to account for higher order organization such as repetition, randomness, and colour. The outcome has helped to provide researchers and image designers with a fast, valid, and reliable estimate of the perceived complexity of any image they might choose to use for research or application purposes.

Visual complexity and beauty

Here, we are interested in accounting for the visual complexity of artistic images because ratings of beauty are thought to depend primarily on judgments of visual complexity and

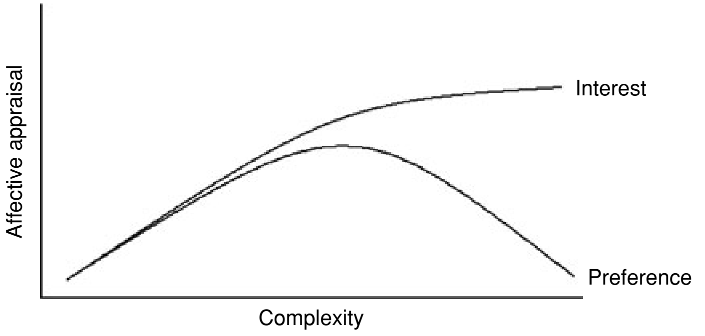

Figure 1. The effect of complexity on preference and interest (Berlyne, 1971).

artistic images contain arrangements of visual elements intended to appeal to the senses or emotions.

In the study of aesthetic processes, the curvilinear relationship between beauty and visual complexity has received the most attention. Berlyne (1970, 1971) argued that preference and interest increase linearly with visual complexity until an optimum level of arousal is reached. At this point, further increases in complexity would elicit a down turn in arousal and preference would decrease (Figure 1). In other words, when visual stimuli are of low complexity preference will also be low. People will seek to maintain a level of arousal that is constant with their preferred level of stimulation. Individuals who are highly aroused will seek out certainty, whereas those low on arousal will seek out more stimulating, less certain, visual environments.

Berlyne's theory has received mixed support because of its poor predictive validity; it is not possible to predict the point of the cusp before it has been reached (see, for example, Krupinski & Locher, 1988; Martindale, Moore, & Borkum, 1990). Even results that reflect some sort of inverted U-shaped distribution (Aitken, 1974; Nicki & Moss, 1975) are limited by sample size; they do not contain sufficient numbers of ambiguous images.

Ecological theory and beauty

The Kaplans (Kaplan, 1995; Kaplan & Kaplan, 1989) offer a complementary explanation to arousal theory by substituting arousal with an information-processing approach. Based on an extension of Gibson's ecological perspective, they argued that humans prefer environments that make sense. Environments affording information and understanding would be preferred to more uncertain environments. Humans would be predisposed to prefer environments that are both interesting (complex) but also coherent (offering a degree of involvement that makes sense). Humans seek out a mixture of coherence and legibility (for understanding), but for exploration we prefer complexity with a degree of obscurity or mystery. Evolutionary research offers some support to the idea that humans prefer moderately complex coherent environments, for example, grasslands with scattered trees (Heerwagen & Orians, 1993; Orians, 1980). This evolutionary preference has been termed biophilia (Fromm, 1965; Kaplan, 1995; Wilson, 1984) and explains the tendency for humans to seek out nature and living organisms.

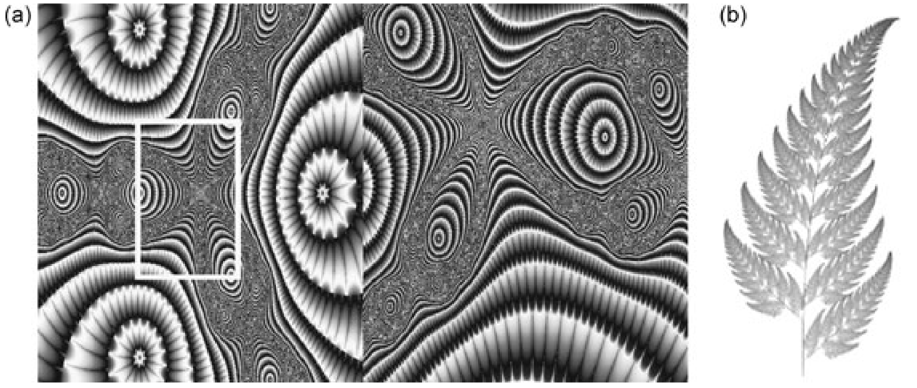

Figure 2. (a) Fractal pattern (showing magnification), (b) Barnsley Fern (1993).

The fractal – a pattern that reoccurs on finer and finer scales – has been demonstrated to capture the visual patterns of the natural world (Figures 2a and 2b). Fractals been described as the 'fingerprints of nature' (Taylor, Micolich, & Jonas, 1999, 2003; Taylor *et al.*, 2007) because their repeating patterns can be found in mountain ranges, coast lines, clouds, rivers, trees, plants, and so on (Gouyet, 1996; Mandelbrot, 1977). There also seems to be some evidence of fractal behaviour in eye physiology. Complicated patterns with few aspects of self-similarity elicit more fractal eye-movement trajectories (Aks & Sprott, 1996). This makes sense from an evolutionary point of view, fractal search patterns are more efficient than random/Brownian trajectories (Taylor, Boydston, & Van Donkelaar (unpublished) cited in Taylor & Sprott, 2008).

It is thought that fractals tap into specialist cognitive modules that have developed to moderate information about living things and that such modules are linked with emotional regulation (Wilson, 1984). Recent research also suggests some brain areas are responsive to fractal patterns. Hagerhall *et al.* (2008) reported that viewing fractal patterns elicited high alpha in areas of the brain concerned with attention and visual spatial processing (the frontal lobes and the parietal area). These studies support research that suggests that training using fractal shapes could help the development of perceptual concepts of the natural, stimulate biophilic responses, and trigger aesthetic interest and restorative responses (Joye, 2005, 2006). The strongest evidence for the application of fractal patterns in therapeutic environments is that fractal patterns reduce physiological stress (Taylor, 1999).

Fractals in art

Fractal geometry has established its usefulness in understanding the structure and authenticity of major works of art. Taylor (2002) having examined film footage of Jackson Pollock at work argued that Pollock was clearly generating paintings with a high fractal dimension (*D*) and that Pollock was actually able to fine-tune the *D* value of his paintings. Detailed analysis of sections of Jackson Pollock's work demonstrated that the fractal dimension of his work increased steadily over a 10-year period (Taylor *et al.*, 1999). Following this analysis, it was possible to de-authenticate recently discovered paintings attributed to Pollock because the dimension values were not consistent with previous works.

Taylor's work may also be useful in addressing some of the shortcomings of the Berlyne (1971) hypothesis (predicting the cusp). Taylor has reported the presence of three categories with respect to aesthetic preference for fractal dimension (Taylor, Newell, Sphehar, & Clifford, 2001). These can be categorized into low preference (1.1–1.2), high preference (1.3–1.5), and low preference (1.6–1.9). Humans are consistent in their preference for fractal images in the 1.3–1.5 fractal dimension regardless of whether these fractals were generated by mathematics (such as Figure 2), humans (e.g., the art of Jackson Pollock), or natural processes (coastlines, trees, or clouds). These categories suggest that the cusp is located at a D value slightly greater than 1.5. However, it remains difficult to untangle how much of the relationship between interest/beauty and visual complexity is intertwined with familiarity, ambiguity, or some other degree of sense making.

The first study reported here examines the extent to which computerized measures of visual complexity (Donderi, 2006a; Forsythe *et al.*, 2003, 2008) are able to capture some of the processes involved in perceiving complexity in art. A valid and reliable measure of visual complexity – a measure that is unaffected by familiarity – can then be used to address the predictability issue in Berlyne's hypothesis. Study 2 examines the utility of the most successful computerized metric in predicting the relationship between beauty and visual complexity and the extent to which fractal dimension can account for some of the processes involved in preference for certain types of art.

STUDY 1: MEASURING VISUAL COMPLEXITY IN ART

Previous research that has attempted to develop an automated measure of visual complexity has focused on utility stimuli such as computer icons, street signs, military symbols (Fleetwood & Bryne, 2006; Forsythe *et al.*, 2003), radar maps (Donderi, 2006b), line drawings of everyday objects, and nonsense shapes (Forsythe *et al.*, 2008).

The study of stimuli with aesthetic value presents a new type of challenge in the measurement of visual complexity. Berlyne (1971) argued that it is possible to simply enjoy art in the form of perceiving patterns that do not exist for any reason other than to be looked at, that nothing else can be done with and that do not give rise to any specific behaviour other than perceptual experience. With this in mind, it is perhaps reductionist to diminish through computerized analysis such experiences. We know that other processes are involved in the formulation of judgments relating to the hedonic value of a picture (Bartlett, 1932; Cupchik, 1992; Feist & Brady, 2004; Furnham & Walker, 2001; McWhinnie, 1993; Rawlings, Barrantes i Vidal, & Furnham, 2000; Russell, 2003; Russell, Deregowski, & Kinnear, 1997).

Therefore, it would seem that the chances of successfully isolating the measurement of one image element and its impact on experiences of beauty is unlikely. Equally, as argued by Berlyne (1971), the components of beauty are complex but psychology should not use this as an excuse for saying very little about the subject.

Visual complexity measures (Jpeg, Gif, and perimeter detection)

Some compression techniques (Donderi, 2006b) present a good approximation of subjective image complexity. Lossy compression using Jpeg is contrasted here with 'lossless' Gif compression. Gif compression works better on pictures with limited colorization (<245) and performs particularly well on sharp transitions. Gif compression can only reduce a file size to about half of its original size. To control for this difficulty, Jpeg compression was also calculated to a 50% compression size.

'Perimeter detection' (PD) correlates strongly with human complexity on line drawings of real-world objects and nonsense shapes and it is able to capture some of the processes important in judgments of subjective complexity. For a full description of how this measure works, see Forsythe *et al.* (2003, 2008). In brief, the PD metric examines sudden changes in intensity occurring at the edges of an image; the more edges the higher the PD score, the more complex an image is.

STUDY 1: VALIDATION OF THE VARIOUS MEASURES OF VISUAL COMPLEXITY

Method

Image selection

The initial pool of stimuli was a set of over 1,500 scanned images, including abstract and representational, as well as artistic and decorative stimuli. Prior studies have emphasized the need to include stimuli of each of these types. Here, our distinction between artistic and decorative stimuli is analogous to Winston and Cupchik's (1992) classification of 'High' art versus 'Popular' art. They noted that 'Popular' art emphasizes the pleasing aspects of the subject matter, whereas 'High' art explores a broader range of emotions and strives to achieve a balance between content and style. Specifically, in our case, artistic stimuli include reproductions of catalogued artworks created by renowned artists and exhibited in museums. Following Heinrich and Cupchik's (1985) recommendations, images belong to different styles, such as realism, cubism, impressionism, and post-impressionism. We used the collection Movements in Modern Art of the Tate Gallery, London, as a guide, and added European XVII and XVIII Century art as well as American Art paintings. Decorative stimuli included photographs of landscapes, artifacts, urban scenes, and so forth, taken from the book series Boring Postcards, Phaidon Press, London, and photographs taken by us, together with a sample of images from the Master Clips Premium Image Collection (IMSI, San Rafael, CA), which are used in industrial design, illustrating books, and so on. On the other hand, half of the artistic and decorative stimuli were abstract. In both cases, the distinction between abstract and representational followed the usual criterion of the presence or absence of explicit content.

The original set of materials was subjected to a series of modifications in order to eliminate the influence of variables such as novelty, or the celebrity of the artworks as well as size and shading. Only relatively unknown pieces were selected. In order to avoid the influence of ecological variables, we eliminated those stimuli that contained clear views of human figures and human faces, as well as those stimuli portraying scenes that could elicit strong emotional responses. To avoid the undesired influence of psychophysical variables, all stimuli were adjusted to the same resolution of 150 ppi. Additionally, the colour spectrum was adjusted in all images. Luminance of the images were measured in a dark room, by means of a Minolta Auto Meter IV F photometer placed at 40 cm from the screen with an accessory for 40° reflected light (for screen specifications please see Participants and procedure). Values of extreme illumination and shadow in each picture were adjusted to reach a global tone range allowing the best

Figure 3. Line drawing, subsection with compression artifacts.

detail. Stimuli were classified according to their dominant tone (dark, medium, or light), and those with a mean distribution of pixels concentrated in both the left (dark) and right (light) extremes of the histogram were discarded. Thereafter the luminance of the stimuli was adjusted to between 370 and 390 lx. Stimuli that could not be reasonably modified according to all of these specifications were discarded. Finally, the signature was removed from all signed pictures. This process of stimuli selection and modification was carried out such that we were left with 800 images:

(1) *Abstract artistic* ($n = 263$). Art catalogued by acclaimed abstract artists that does not depict objects but uses colour and form in a non-representational way, for example, Pollock, Mondrain, Rothko, Newman, etc.
(2) *Abstract decorative* ($n = 141$). Shapes and forms used in industrial design, advertising (e.g., Figure 3).
(3) *Figurative representational* ($n = 148$). Art catalogued by acclaimed abstract artists that represent the real world (Matisse, Manet, Cezanne, Guaguin).
(4) *Figurative decorative* ($n = 48$). Pictures of objects used in industrial design, adverting, etc.
(5) *Environmental scene photographs* ($n = 200$). Both natural and man-made content.

Participants and procedure

Two hundred and forty (112 men and 128 women) participants from the University of the Balearic Islands without formal artistic training took part in the study. The participant's first language was Spanish. The 800 images were divided, following a stratified sample into 8 sets of 100 images. Each set was presented to a different group of 30 participants and the presentation order was randomized. Images were inserted in PowerPoint at a pixel size of 710×530 and presented by PC (Dell Optiplex 760) and displayed on a screen (400 cm $\times$ 225 cm; ratio 16:9). Participants were seated between 200 and 700 cm from the visual display.

The images were present for 5 s and participants recorded their responses. Participants were asked to rate these pictures on a Likert scales from 1 to 5. A score of 5 was an image that was judged to be very complex, a score of 1 was an image that was judged to be very simple. Participants were given a definition of complexity as 'the amount of detail or intricacy' (Snodgrass & Vanderwart, 1980).

Table 1. Correlations between different measures of visual complexity

	Subjective complexity	Perimeter	Jpeg
Abstract artistic ($n = 263$)			
Perimeter	.39		
Jpeg	.51	.84	
Gif	.42	.69	.75
Abstract decorative ($n = 141$)			
Perimeter	.40		
Jpeg	.54	.69	
Gif	.60	.40	.78
Figurative ($n = 148$)			
Perimeter	.37		
Jpeg	.40	.86	
Gif	.47	.74	.83
Figurative decorative ($n = 48$)			
Perimeter	.63		
Jpeg	.65	.88	
Gif	.70	.81	.77
Natural pictures ($n = 200$)			
Perimeter	.54		
Jpeg	.60	.87	
Gif	.55	.75	.90

Note. All correlations significant $p < .01$.

Results

(i) Validation of the various measures of visual complexity

Human judgments of visual complexity were correlated with the two measures of image compression (Gif and Jpeg) and the edge detection measure 'Perimeter detection'. Human judgments correlated significantly with Gif ($r_s = .74$, $p < .01$), and Jpeg compression ($r_s = .65$, $p < .01$) and PD ($r_s = .58$, $p < .01$). When separate analyses were performed for the different picture types (Table 1), Gif compression more frequently was the larger correlate. Gif was the larger correlate for abstract decorative images ($r_s = .60$, $p < .01$), for figurative art ($r_s = .47$, $p < .01$), and for figurative decorative art ($r_s = .70$, $p < .01$). Jpeg was the largest correlate for abstract artistic pictures ($r_s. = 51, p < .\ 01$) and natural pictures ($r_s = .60, p < .01$). The computerized measures tended to correlate significantly with one another suggesting that to some degree they were tapping similar constructs.

Discussion

Gif compression correlated most strongly with human judgments of visual complexity ($r_s = .74, p < .01$), followed by Jpeg ($r_s = .65, p < .01$) and PD ($r_s = .58, p < .01$). Previous studies (Donderi, 2006a; Forsythe *et al.*, 2003, 2008) have not found Gif compression to have an advantage over other computerized measures, however image sets used in those studies were utility devices (icons, symbols, radar screens) and sample sizes tended to be much smaller (some 800 images were used in this study).

Different computerized measures perform more effectively for different types of images. For example, the Gif advantage deteriorated for images containing high levels of colourization (e.g., abstract art) and for natural images. Gif compression is known to work better on pictures with limited colourization, or sharp transitions possibly explaining why this measure correlated highly with human judgments in sets of simpler images, for example, abstract decorative pictures ($r_s = .60$, $p < .01$) and figurative decorative pictures Gif ($r_s = .70$, $p < .01$). The measure also performed well – relative to other image types – on much more complex images such as figurative art ($r_s = .47$, $p < .01$). One reason for this improved performance may be the way in which Gif permits reconstruction of an original image from the compressed file (Taubman & Marcellin, 2001). Jpeg removes small details and fine edges and is prone to the addition of 'compression artifacts' (Figure 3), these are random details which could artificially inflate a compression file size.

Conclusion

Visual complexity is thought to be one of the most important contributors to perceived beauty in art (Berlyne, 1971) but human judgments of visual complexity are not necessarily reliable (Forsythe *et al.*, 2008). A 'still life' traditionalist painting of an apple may be created to contain the same elements, lines, and colours, as a cubist painting of an apple, but the former would receive lower complexity ratings because it were more familiar to the viewer. Familiarity acts as a mediating variable reducing its perceived complexity.

Gif compression has presented as a strong correlate with human judgments of complexity in artistic images. The second study reported here applies Gif to test the Berlyne (1971) hypothesis and then in the study of other contributing factors in the perception of beauty (for example, colour and self-similarity).

STUDY 2: BEAUTY, COMPLEXITY, AND FRACTAL DIMENSION

Beauty and complexity

Beauty and/or interest are thought to depend, primarily on judgments of visual complexity. Berlyne's (1971) hypothesis of a curvilinear relationship between preference and complexity is tested here using a computerized measure of visual complexity (Gif). Computerized measures can account for colourization and randomness in an image and they are also unaffected by higher order cognitive processes such as the degree to which a viewer is familiar with the presented image. We predict that some degree of curvilinear relationship between beauty and visual complexity (Gif) will be evident but that this will differ slightly from the results of previous research because the measures used in previous studies may have been influenced by familiarity with the images in question and the types of images selected for testing. Previous studies omitted from analysis, a wide range of images particularly images that were ambiguous in nature (Aitken, 1974; Nicki & Moss, 1975). Taylor and Sprott (2008) addressed this latter problem by testing the relationship between the visual complexity of mathematical fractals (such as Figure 2a) and judgments of beauty. They found no significant correlation between the two variables suggesting that other visual parameters such as geometry are equally important.

Representational art is consistently preferred over abstract art and design (McWhinnie, 1987 and others), possibly because as the object becomes more meaningful, less effort is required for interpretation (Bartlett, 1932; Russell, 2003). If individuals have a predisposition to prefer natural images (Kaplan, 1995; Kaplan & Kaplan, 1989) and images that are meaningful, familiar, or organized (Bartlett, 1932; Russell, 2003) then the study of these images alone will tell us very little about the extent to which visual complexity plays a key role in perceived beauty. In an attempt to address some of the shortcomings of pervious studies (Aitken, 1974; Nicki & Moss, 1975), we examine changes in beauty, fractal dimension, and visual complexity across different picture categories; abstract, representational, and photographs of naturally occurring scenes.

Colour is also a significant feature in art and will doubtless contribute to judgments of beauty. To control for the extent to which colour contributes to judgments of beauty within a piece of art (and thus further isolate the contribution of visual complexity and fractal dimension) two sets of pictures were created (colourized and greyscale). This will enable direct comparisons between judgments of beauty in colourized images and their greyscale conversions.

Beauty, complexity, and fractals

Fractals are 'rough or fragmented geometric shapes that can be subdivided in parts, each of which is (at least approximately) a reduced-size copy of the whole' (Mandelbrot, 1977). This property, referred to as self-similarity, means that any portion of a curve, when magnified in scale, would appear almost identical to the whole curve. The fractal dimension is the measure to which a fractal 'fills a space', a phenomenon observable at increasing magnitudes.

A coastline is a one-dimensional fractal because it is a line (i.e., its topology is one dimensional). The repeating patterns in this line cause it to spread across two-dimensional space, and hence the fractal dimension lies between 1 and 2. A mountain is a two-dimensional fractal because it is a surface (i.e., its topology is two-dimensional). The repeating patterns in this surface spread across three-dimensional space and hence the fractal dimension is expected to lie between 2 and 3.

Fractal dimension is also related to visual complexity. If we were to magnify images with a low fractal dimension they would remain smooth in appearance. High D images on magnification would however appear more coarse and complex (Cutting & Garvin, 1987; Gilden, Schmuckler, & Clayton, 1993; Pentland, 1984). We hypothesize that taken together, measures of visual complexity and fractal dimension will be able to account for more of the variance in judgments of perceived beauty than judgments of visual complexity alone.

Method

Calculating fractal dimension

The notion of 'fractional dimension', D, provides a way to measure the roughness or convolution of fractal curves. The dimension of a line, a square, and a cube is easy to calculate (one, two, and three, respectively). Roughness can be thought of as an increase in dimension: a rough curve has a dimension between 1 and 2, and a rough surface has a dimension somewhere between 2 and 3. There are various methods for measuring fractal dimension, D, and all are based on a power law that generates scale-invariant properties (Taylor & Sprott, 2008). Physical objects (for example, natural phenomena) are also range restricted.

The fractal dimension D may be any real number between 1 and 2 and is defined by:

$$D = \frac{\log(L2/L1)}{\log(S2/S1)}$$

$L1$, $L2$ are the measured lengths of the curves (in units), and $S1$, $S2$ are the sizes of the units (i.e., the scales) used in the measurements.

D *measurement of picture*

The D of each image was calculated using ImageJ (http://rsbweb.nih.gov/ij/index.html), a public domain Java image-processing program developed by the National Institute of Mental Health. The box-counting dimension is widely used because it can measure images that are not entirely self-similar. Each image was converted to black and white using the binary threshold algorithm within ImageJ. This method was used in order to prepare each image for the fractal analysis of its fundamental geometric features.

To calculate the box-counting dimension, an image must be placed on a grid scale. The x-axis of the grid is S where $S = 1/(\text{width of the grid})$. For example, if the grid is 240 blocks high and 120 blocks wide, $S = 1/120$. One then counts the number of blocks that the image touches (this is N(s)) and any blocks that are empty. The grid is re-sized to a finer magnification and the process repeated. Different magnifications can then be compared. In this case, the numbers of squares (N) (painted content, brush strokes, lines, etc.) is counted as the magnification is reduced and consequentially the size of the squares (L). Fractal patterns are determined by $N(L)$ through a power law relationship [$N(L) \sim L{-}D$] that generates scale invariance. D values range between 1 and 2 and the values are often plotted on a graph where the x-axis is the log(S) and the y-axis is the log(N(s)). A linear relationship between these two is an indication of self-similarity. For example, Figure 4 illustrates the log–log plot for Dali's 'The Face of War'.

The level of definition for the fractal analysis was based on two considerations. First, some of the images to be analysed were in the Pointillistic tradition, for example, in the work of Georges Seurat, 'Models' cira: 1887–88), where some of the strokes are small distinct dots of colour. It was necessary to use a level of detail that would accommodate analysis of the works of artists in this tradition. It was also necessary to use a level of

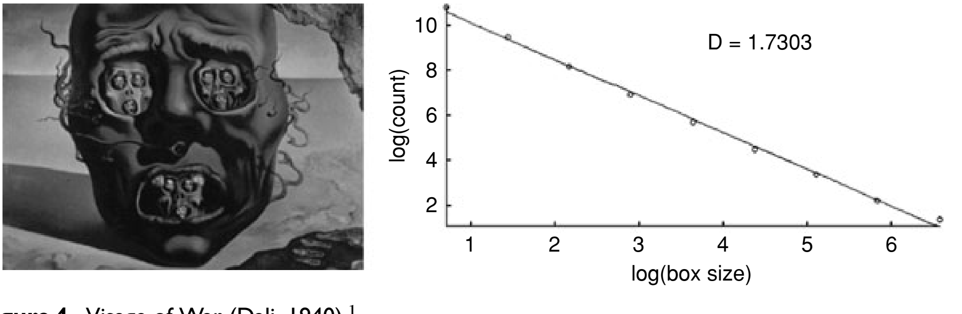

Figure 4. Visage of War (Dali, 1940).[1]

detail for the analysis of the works of others. For example, (Figure 4[1]) Dali's 'The Face of War' (1940) is more conspicuously self-similar and does not fall within the Pointillistic tradition.

Second, in order to obtain a standard measure of fractal dimension using the box-counting method it was necessary, for purposes of comparability, that the same level of definition be applied to the whole image set. In order to do this a random sample of 100 images was taken across each of the traditions and fractal analysed. The box counts were initially set at: 2, 4, 8, 16, 32, 64, 128, 256, 512, 1,024. We manually back-tracked from a box count of 1,024 to 720 because beyond this level of definition there were no there no statistical differences in D to the fourth decimal place, the intra-reliability was $r = 1.00$. Thus, the box sizes for all images were set between 1 and 720. ImageJ binary threshold conversion was used for all images. Each image was also visually inspected – in particular an inspection for how the algorithm determined foreground and background. On the occasions where there was ambiguity as to foreground and background (for example, in abstract art), we took a mean D between the two perspectives.

Materials, procedure, and participants

Gif complexity was chosen as a selection variable, with relative numbers of images at each interval of complexity. Initially random selection produced a data set with few very complex and few very simple images. Previous studies have been criticized for having limited data sets with very few simple or complex images (Aitken, 1974; Nicki & Moss, 1975). This sample set was increased by purposefully selecting all images with very small complexity values and very large complexity values.

This selection resulted in a data set that had a larger number of abstract images ($n = 240$, selected from the pool of 800). Other categories included:

- Natural environments (forests, animals; $n = 21$) and man-made environments (houses, cityscapes; $n = 28$).
- Abstract art by acclaimed artists ($n = 64$) and pictures used in industrial design (abstract decorative $n = 70$).
- Figurative artistic pictures by acclaimed artists ($n = 38$) and decorative pictures used in industrial design and advertising (figurative decorative $n = 19$).

The 240 images were randomly divided into 3 sets (73, 70, and 97 images) and 4 duplicates were added to each set for consistency checks. No differences were found across the data set between images previously presented and their subsequent duplicates. An additional set of greyscale conversions was created from one subset of the 240 pictures ($n = 97$). In total, this created four groups of images. Each set was presented to a different group of 30 participants who rated the pictures for beauty.

Participants were asked to rate the beauty of pictures on a Likert scale from 1 (not at all beautiful) to 5 (very beautiful). Viewing conditions, luminance and other stimuli controls were as Expt 1. The images were presented for 5 s and participants recorded their responses. Participants were university undergraduate students, whose first language was English ($n = 120$ participants: 4 groups $\times$ 30 participants).

[1] *Low-resolution reproduction for scholarly commentary (under fair usage). Face of War was not used in the original 800 image set because of its notoriety. It is used here purely as an example of an obviously fractal image.*

Results

The distribution of one or two of the measures presented either a skewed or kurtotic distribution. Reanalysis of the transformed data ($\log_{10}$) made no difference to the outcome of subsequent analyses, and therefore analysis as reported is from the untransformed data. Pictures of the natural environment were considered on average most beautiful (3.45), most complex (310,125.10), and had the highest fractal dimension (1.81). Abstract decorative pictures were rated as least beautiful (1.69), least complex (57,277.77), and least fractal (see Table 2).

(i) Beauty and complexity: Testing the Berlyne inverted 'U' hypothesis

Gif complexity was standardized onto a five-point scale using histogram equalization: into five intervals (or quintiles). This transformation permitted direct comparisons with the five-point beauty scale. A one-way analysis of variance with judgments of beauty as the dependent variable and standardized Gif scores as a factor presented a significant main effect $F(4, 235) = 49.30$, $p < .01$ ($\eta^2 = .47$). *Post hoc* (Tukey HSD) level 1 is statistically different from all other levels ($p < .01$). Level 2 is statistically different from all levels, except 5.

Figure 5 illustrates the trend between human and computerized measures. As predicted by Berlyne (1971), there is an inverted U shape pattern, although the data

Table 2. Descriptive statistics (colour images)

	Mean	*SD*	Skew	*SE*	Kurtosis	*SE*
Abstract artistic (*n* = 64)						
Beauty	2.49	−0.48	1.08	.30	1.04	.59
Fractal *D*	1.77	0.06	−2.20	.30	6.40	.59
Gif	304,192.23	85,786.58	−0.29	.30	0.33	.59
Abstract decorative (*n* = 70)						
Beauty	1.69	0.35	0.83	.29	0.30	.57
Fractal *D*	1.57	0.18	−0.50	.29	−0.09	.55
Gif	57,277.77	33,893.91	1.37	.29	2.12	.55
Figurative artistic (*n* = 38)						
Beauty	3.28	0.65	−0.67	.38	1.04	.75
Fractal	1.78	0.06	0.41	.38	1.17	.75
Gif	281,835.42	47,452.27	−0.28	.38	0.64	.75
Figurative decorative (*n* = 19)						
Beauty	2.35	1.01	0.33	.52	−1.34	1.01
Fractal	1.73	0.09	−1.24	.52	−0.86	1.01
Gif	214,213.95	79,347.49	−0.54	.52	−0.70	1.01
Natural environments (*n* = 21)						
Beauty	3.45	0.42	−0.21	.50	−1.4	.97
Fractal *D*	1.81	0.04	0.42	.50	1.15	.97
Gif	310,125.10	58,052.22	−1.31	.50	2.81	.97
Man-made environments (*n* = 28)						
Beauty	2.49	0.84	0.26	.44	−1.40	.86
Fractal *D*	1.76	0.09	−0.86	.44	1.37	.86
Gif	250,696.21	55,572.85	0.48	.44	0.20	.86

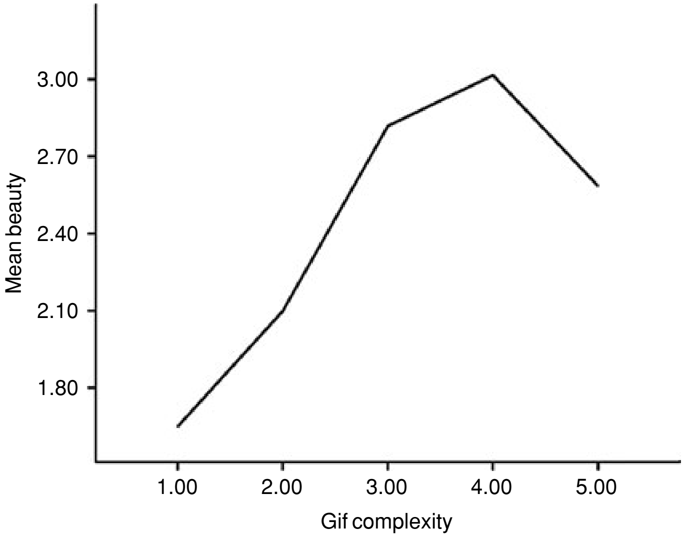

Figure 5. Beauty and Gif complexity (all pictures).

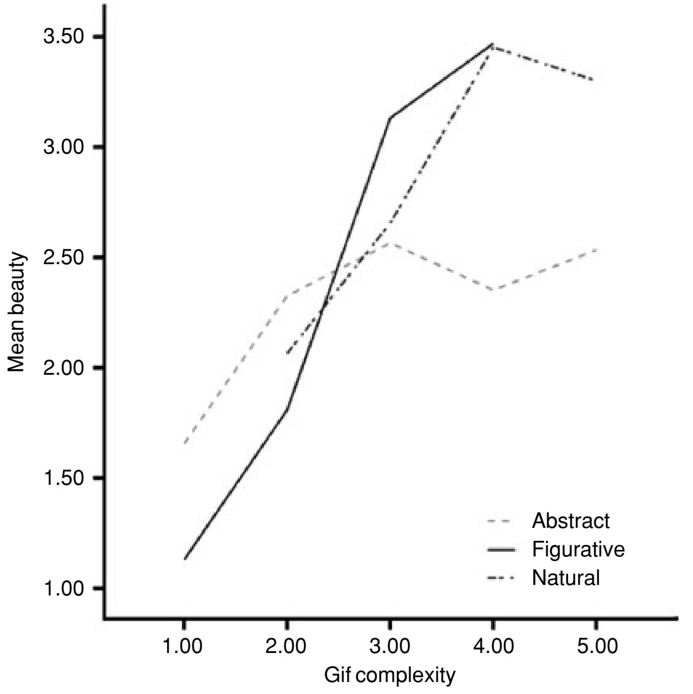

Figure 6. Beauty and Gif complexity (natural, abstract, representational).

in this study suggests that the increase in beauty judgments is slightly shaper than would be predicted, with the cusp for preference occurring slightly later. The means plot of picture categories (Figure 6) presents a linear complexity trend for all categories, except abstract. These results suggest that abstract paintings are considered less beautiful

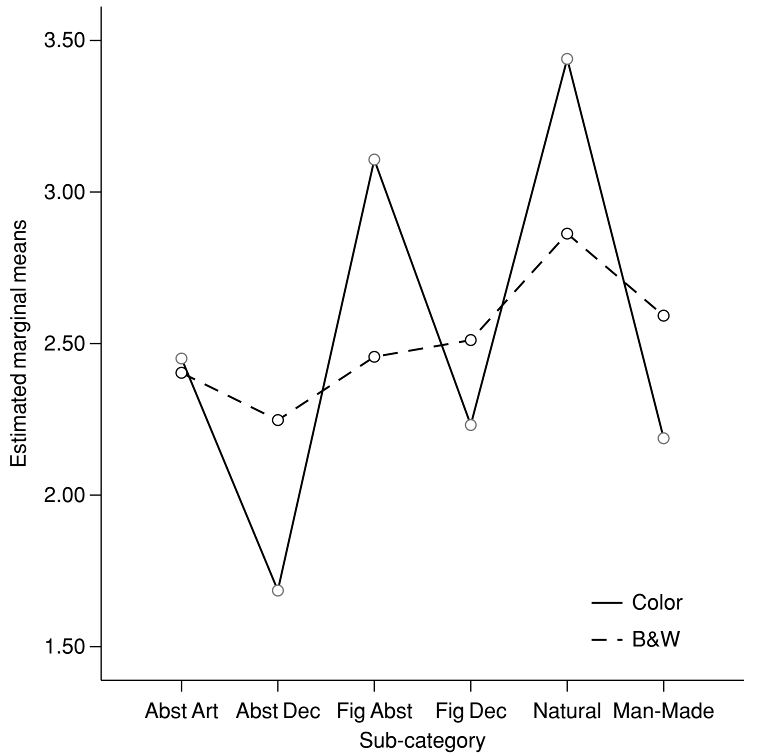

Figure 7. Mean differences in judgments of beauty across image category.

because of their non-identifiable content and that the visual complexity of these images plateaus around the mean.

(ii) Picture category and colour

Independent samples t test showed no significant difference between colourized images and their greyscale versions. Figure 7 illustrates the trend in beauty judgments between picture subcategory and image type (greyscale or colour). The greyscale image set tends to be rated as similarly beautiful across all categories. The same set of colourized pictures shows much more variation across picture category. The reduced variance across the greyscale data set suggests that colour is a key component when observers are attempting to rate a picture for beauty.

(iii) Fractal dimension, image complexity, and beauty

Gif complexity (unstandardized scores) and fractal dimension were regressed onto the dependent variable 'beauty'. Both made a statistically significant contribution to the regression equation, $R^2 = .42$, $F(2, 237) = 83.76$, $p < .00$ (tolerance .59, VIF 1.70). Together, these variables accounted for 42% of the variance in judgments of beauty. The largest predictor was Gif complexity $\beta = 0.53$, $t(237) = 8.13$, $p < .01$, followed by fractal dimension, $\beta = 0.17$, $t(237) = 2.65$, $p < .01$.

Separate analyses were preformed on the three broad image categories, with Gif complexity and fractal dimension regressed onto the dependent variable beauty. There were significant effects in all three categories: abstract art, $R^2 = .47$, $F(2,131) = 59.62$, $p < .01$; figurative art, $R^2 = .55$, $F(2, 54) = 33.98$, $p < .00$; and natural images, $R^2 = .25$, $F(2, 46) = 7.59$, $p < .00$. Gif complexity was a significant predictor for all picture sets; abstract, $\beta = 0.55$, $t(131) = 6.80$, $p < .01$; figurative, $\beta = 0.75$, $t(54) = 7.38$, $p < .00$; and natural, $\beta = 0.31$, $t(46) = 2.31$, $p < .05$. Fractal dimension contributed significantly to predictions of beauty for abstract images, $\beta = 0.19$, $t(131) = 2.40$, $p < .00$ and the natural image picture set, $\beta = 0.30$, $t(46) = 2.20$, $p < .05$.

Discussion

Until Berlyne (1970, 1971), it was generally believed that beauty could not be measured. Berlyne argued that preference for an object would increase by a function of visual complexity, that after a point complexity would cause over stimulation and preference would decrease. Many studies have reported a significant relationship between beauty and complexity and some have not. Others report that the trend is wholly linear (see Nadal, 2007, for a review). Inadequate sampling (Aitken, 1974; Nicki & Moss, 1975) and the ability to capture what exactly appears complex or simple (Van Damme, 1996) has almost certainly contributed to the inconsistency in findings.

The visual complexity measure (Gif) applied here is particularly useful because it takes into consideration not only the additive values of lines and elements, but it also operates at a higher level accounting for the organizing principles that mediate randomness (such as order and symmetry). This measure will account for the extent to which different colours are used, and how those colours are organized. In short, the Gif compression technique is able to produce a good approximation of what humans do when they perceive stimuli. Using this measure, over a range of different picture types varying in visual complexity, we have been able to determine some support for Berlyne (1970, 1971). Figure 5 illustrates the relationship between judgments of beauty and this measure of visual complexity. Our results suggest that the cusp occurs later, and that for certain picture types the relationship is linear.

Berlyne's (1970, 1971) framework for the exploration of aesthetics through concepts such as beauty and arousal has become a reference point for most contemporary aesthetic research, but we still understand very little about what makes a piece of art beautiful. Picture colour is often argued as an important determinant of aesthetic appreciation (Maffei & Fiorentini, 1995; Martindale & Moore, 1988). The relative impact of colour as to spectral intensity has in this case been difficult to quantify, raters were unable to differentiate beauty between different greyscale pictures and most pictures were rated similarly beautiful. Colourized pictures showed much more variation across picture category. This is because colour adds interest, variety, and intensity. The artist utilizes structure, colour, and even physical gestures (for example, Pollock's dripped paintings, or the brush marks of Monet) to communicate to the observer. These properties work together to create a higher-level construct. Removing a significant element such as colour changes the essence of the picture and the message is lost.

Naturalness has also been argued as being a strong preference variable. Natural objects have a high degree of fractal content (Gouyet, 1996; Mandelbrot, 1977) and humans have a preference for such environments (Kaplan & Kaplan, 1989). These hypotheses were supported here; pictures of natural environments were on average more beautiful and more fractal than other images (Table 2) and fractal dimension accounted for 30% of the variance in judgments of the beauty of natural scenes and 19% of the variance in images with no semantic content (abstract art). Taken together, visual complexity and fractal dimension tell us something about what makes an image beautiful. Complexity consistently explains more of the variance (53% across all images sets) but fractal dimension still has something to tell us.

Taylor *et al.* (2001) offer a solution to criticisms pertaining to the predictive value of the Berlyne (1970, 1971) hypothesis. They suggest that pictures in the fractal dimension of 1.3–1.5 will obtain much higher preference ratings at lower fractal dimensions (1.1–1.2) and also at higher dimensions (1.6–1.9). When Taylor *et al.*, made these predictions their stimuli were designed to vary across fractal dimension with little non-fractal information: they were derived from cropped sections from Jackson Pollock's drip paintings, mathematical fractals (in the mode of Figure 2a), and naturally occurring fractals (trees, mountains, waves). The pictures in Expt 2 contained both very high and very low fractal content.

When examining the fractal dimensions of all 800 pictures tested here only 6 pictures fell within the fractal dimension 1.1–1.2, 65 pictures fell within the hypothesized preference range (1.3–1.5), and the remaining 729 pictures had a mean fractal dimension of between 1.6 and 1.9. This hypothesis suggests that these latter 729 pictures that should be of low preference. Given that most artistic pictures within this set have higher fractal values than the hypothesized preference range the theory could not be fully tested. One approach would be to collect a range of acclaimed pictures by artists such as Monet, Botticelli, and Van Gogh. Paintings by such artists have remained popular and respected for a long time and were not included in our data set. *A priori* analysis of several well-known paintings and their fractal dimensions are listed below. None have a value falling within the Taylor *et al.* (2001) hypothesized preference range.

Coming from the Mill, Laurence Stephen Lowry (1.8026)
The Face of War, Salvador Dali (1.7073)
The Water Lilies, Claude Monet (1.7846)
The Birth of Venus, Sandro Botticelli (1.8550)
The Sunflowers, Vincent Van Gogh (1.7570)
Netherlandish Proverbs, Pieter Breugel (1.8955)

However, as the results here demonstrate, fractal dimension alone cannot account for judgments of beauty. The current study demonstrated that – even though there is a relationship between visual complexity and fractal dimension (an image with a high D will contain more fine structure) – visual complexity contributes the largest proportion of the variance in aesthetic judgments. Fractal dimension is much more important when judgments relate to natural phenomena.

GENERAL DISCUSSION

There has been a resurgence of interest in the possibility of developing a robust, unbiased measure of visual complexity that can be obtained quickly and cheaply. To date, the catalyst for the development of these measures has been to measure visual complexity in industrial settings. For example, Donderi (2006b) found Jpeg to be a good approximate of judgments of the visual complexity of radar screens and Forsythe *et al.* (2003) developed a perimeter measure of the visual complexity for icons and symbols and measures that can be applied to archives of pictures for neurological and cognitive testing (Forsythe *et al.*, 2008). Here, we compared the performance of three automated measures of visual complexity in art. These pictures ranged across a number of genres, including the graphical, the artistic, and the photographic and also in the way in which the content was expressed (i.e., abstract or representational).

Overall results suggest that applying a Gif compression technique will generally yield a complexity measure that is close to human judgments of visual complexity. When more specific analyses of different picture types are required there are some minor differences between Gif and Jpeg compression that may be of interest to the researcher (Table 1). One reason why Gif compression is perhaps more successful is the way in which it compresses information. Nothing is added or removed, permitting an exact reconstruction of the original image and consequently a more mathematically accurate measure of the number of elements (or compression size) within the image.

Compression techniques such as Gif and Jpeg offer researchers the most reliable and user-friendly option for the quantification of visual complexity, they are also unbiased – they are not affected by familiarity (Forsythe *et al.*, 2008). These metrics have a well-established underlying theoretical basis (information theory) and produce good approximations of human judgments.

In Expt 2, the automated measure facilitated a re-analysis of the Berlyne hypothesis (1970, 1971). As Figures 5 and 6 illustrate, applying an automated measure of visual complexity presents a point of preference that is somewhat different than Berlyne would have predicted; the increase preference is quite marked and there is no gradual decline. One explanation is that previous ratings of visual complexity were influenced by the familiarity of the image. There is a universal preference for representational art (Aitken, 1974; McWhinnie, 1987), viewers prefer images that look like 'something'. Real-world objects will afford more grouping processes and symmetry, all of which will reduce the impact of visual complexity. With these points in mind, one could speculate that the abstract decorative and artistic images – having little or no representational content and being the least preferred – are less likely to be susceptible to a familiarity bias. When participants were asked to rate the complexity of these pictures they would have been able to act to some degree as a computer would. This suggests that the pattern for abstract images illustrated in Figure 5 perhaps more closely represents the relationship with preference and complexity. However, colour may also interact in some way with the abstract image to convey mood and emotion enhancing or attenuate the complexity of the picture and this study was unable to isolate this effect.

There is no evidence that Salvador Dali was aware of fractals or Fractal geometry at the time he painted Visage of War. Yet he was one of the first painters to explicitly incorporate fractal structures into his paintings beginning with *Visage of War*, 1940 (Figure 4). Fractal dimension combined with ratings for visual complexity accounts for more of the variance in judgments of beauty than visual complexity alone. This relationship however requires further exploration; whilst we have presented results suggesting that fractal patterns contribute to judgments of beauty, pictures where viewers are perhaps more ambivalent can also have similarly high fractal dimension scores. This suggests that the combined impact of fractal dimension, visual complexity, and other picture constructs – such as colour – requires further exploration; with the caveat that pictures generally considered universally beautiful (e.g., Sunflowers, Van Gogh, The Birth of Venus and Botticelli) have fractal scores above the hypothesized Taylor range.

Conclusions

Here, we evaluated an automated measure of visual complexity as an unbiased measure of complexity in art works. Gif compression presents a good approximation of visual complexity across a number of image types and may offer researchers a fast and effective alternative to human judgments. Fractal dimension combined with complexity (Gif) is able to account for more of the variance in judgments of perceived beauty in visual art than measures of complexity alone. However, further work is required to explore both the hypothesized ranges of preference in art (Taylor *et al.*, 2001) and the interplay between complexity, colour, and preference.

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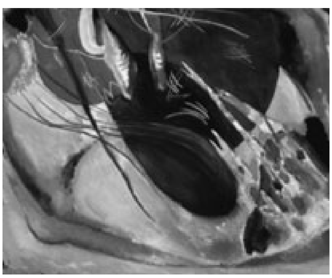
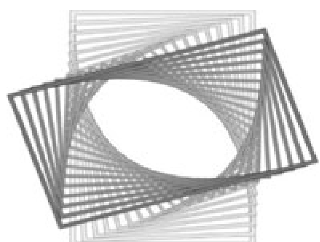
Appendix

Examples of picture types



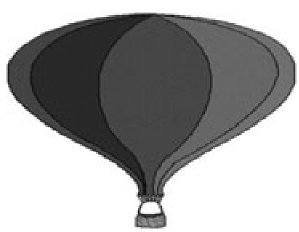
Abstract artistic



Abstract decorative

Natural

Figurative artistic



Figurative decorative

Natural (man-made)