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Artists portray human faces with the Fourier statistics of complex natural scenes

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Abbreviated title: Fourier statistics of human face portraits by artists

Abstract

When artists portray human faces, they generally endow their portraits with properties that render the faces esthetically more pleasing. To obtain insight into the changes introduced by artists, we compared Fourier power spectra in photographs of faces and in portraits by artists. Our analysis was restricted to a large set of monochrome or lightly colored portraits from various Western cultures and revealed a paradoxical result. Although face photographs are not scale-invariant, artists draw human faces with statistical properties that deviate from the face photographs and approximate the scale-invariant, fractal-like properties of complex natural scenes. This result cannot be explained by systematic differences in the complexity of patterns surrounding the faces or by reproduction artefacts. In particular, a moderate change in gamma gradation has little influence on the results. Moreover, the scale-invariant rendering of faces in artists' portraits was found to be independent of cultural variables, such as century of origin or artistic techniques. We suggest that artists have implicit knowledge of image statistics and prefer natural scene statistics (or some other rules associated with them) in their creations. Fractal-like statistics have been demonstrated previously in other forms of visual art and may be a general attribute of esthetic visual stimuli.

Introduction

The fundamental nature of esthetic judgement remains unkown, despite attempts by artists, philosophers and psychologists to define universal principles that characterize what makes art esthetically pleasing to human observers. Several scholars in the field have argued that all humans share the same concept of beauty (Adorno 1970; Burke 1757; Hume 1757; Kandinsky 1912; Kant 1790; Paul 1988; Schelling 1907) and some have concluded that biological factors must be taken into account in order to explain esthetic experience (Burke 1757; Paul 1988). More recently, in the emerging field of neuroesthetics, neuroscientists speculated that esthetic experience is a product of brain function and is closely linked to perceptual processes (Cavanagh 2005; Gregory et al. 1995; Livingstone 2002; Rentschler et al. 1988; Werner and Ratliff 1999; Zeki 1999). Following this general idea, we hypothesized that esthetic art is a phenomenon of resonance between the artist's visual system and his creations (Redies 2008). In our model, this resonant state of neural activity is purposefully induced by the artist through a constant feed-back between the work of art being created and the artist's visual system.

In a search for possible neuronal mechanisms that are linked to esthetic perception, we previously measured Fourier statistics in graphic art from diverse periods and countries of the Western hemisphere (Redies et al. 2007). Results showed that, on average, artists create their works of art with fractal-like statistical properties, independent of the cultural variables present in the set of images analyzed. These fractal-like properties are reflected in a $1/f^2$ Fourier power spectrum (or $1/f$ amplitude spectrum; f: spatial frequency) and imply that works of graphic art display scale invariance. Similiar fractal-like statistical properties have been demonstrated for natural scenes (Burton and Moorhead 1987; Field 1987; Olshausen and Field 2004; Ruderman, 1997; Ruderman and Bialek, 1994; Simoncelli and Olshausen 2001; Tolhurst et al. 1992).

Fractal structure was previously detected in the abstract paintings by Jackson Pollock (Taylor et al. 1999), and image statistics similar to those of natural scenes have been found also in a set of color paintings from diverse Western and Asian cultures (Graham and Field 2007). Moreover, human observers show a general preference for fractal-like structures in landscape silhouettes (Hagerhall et al. 2004). We proposed that this similarity between natural scenes and esthetic visual art relates to the fact that both types of stimuli can be perceived as beautiful by human observers (Redies et al. 2007; Redies 2008).

In the present study, we examined a favorite subject matter of artists, human faces. Photographic images of human faces do not display fractal-like, scale-invariant statistics and the slope of the curve in the log-log plot of spectral power (amplitude squared) versus spatial frequency is steeper than for natural scenes (Bosworth et al. 2006; Torralba and Oliva 2003). We asked whether artists render human faces with the same statistics as photographs of faces. Our results for a large set of graphic art of Western provenance show that this is not the case. Paradoxically, artists portrait human faces with scale-invariant Fourier statistics that are characteristic of complex natural scenes. This finding suggests that artists might have implicit knowledge of complex scenes statistics (or of unknown rules associated with complex scene statistics) and prefer these statistics or rules in their creations.

Material and Methods

Image Data

Two photographic face databases (1, 2), a natural scene database (3) and two databases containing portraits by artists (4, 5) were analyzed.

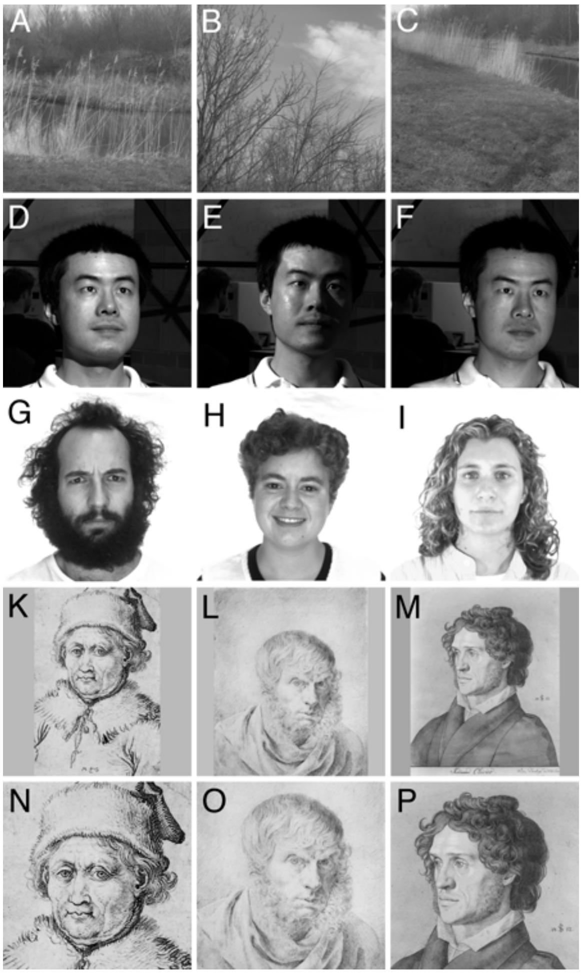

Figure 1. Examples of the images analyzed. *A-C*. Examples from the Groningen database of natural scenes (van Hateren and van der Schaaf 1998). *D-F*. Examples from the Yale face database B (Georghiades et al. 2001). *G-I*. Examples from the AR face database (Martinez and Benavente 1998). *K-L*. Examples of padded images of monochrome portraits by artists (*K*, drawing by Martin Schongauer, about 1465; *L*, drawing (self-portrait) by Caspar David Friedrich, 1820; and *P*, drawing by Julius Schnorr von Carolsfeld, 1817. *N-P*. Details displaying the face with an eye distance similar to that of the photographic faces in *D-I*. Slope constants and deviations from the fitted line (in parentheses) were: *A*, –1.93 (0.005); *B*, –1.73 (0.002); *C*, –2.00 (0.008); *D*, –3.37 (0.003); *E*, –3.31 (0.004); *F*, –3.28 (0.001); *G*, –3.50 (0.048); *H*, –3.69 (0.005); *I*, –3.68 (0.124); *K*, –1.84 (0.008); *L*, –1.96 (0.046); *M*, –2.30 (0.024); *N*, –1.84 (0.031); *O*, –1.87 (0.043); and *P*, –2.09 (0.041). The images shown in *K-M* were reproduced with permission from "Das Berliner Kupferstichkabinett", Akademischer Verlag, Berlin, 1994 (inventary numbers: *K*, 976-1; *L*, 916-2; and *M*, 5212; © Staatliche Museen zu Berlin, Kupferstichkabinett).

(1) The Yale face database B (Georghiades et al. 2001) consists of monochrome images of 10 people that were photographed with 9 different poses under 64 illumination conditions in front of a simple laboratory or office background. Original images were 640 by 480 pixels.

(2) The AR face database (Martinez and Benavente 1998) contains color images of 126 people with different facial expressions, illumination conditions and occlusions, photographed on a uniformly bright background. Image size was 768 by 576 pixels. Images were converted to grayscale values.

Centered passport-type details of 480 by 480 pixels (Yale face database) or 576 by 576 pixels (AR face database) were cut from each image for analysis. Examples are shown in Figure 1D-I.

(3) For comparison, images from the Groningen natural scene database (van Hateren and van der Schaaf 1998) were analyzed. The same dataset of 208 images analyzed previously (Redies et al. 2007) was used. Centered details of 1024 by 1024 pixels were cut from the original monochrome images of 1536 by 1024 pixels. Examples are shown in Figure 1A-C.

(4) A database of 306 portraits by artists was generated. Reproductions were digitized from various art books by a calibrated scanner (Perfection 3200 Photo, Seiko, Epson Corporation, Nagano, Japan). No compression or image enhancement algorithms were applied. Images were scanned in 8-bit grayscale at a resolution of at least 1024 pixels width and length. The database consisted of monochrome or lightly colored (washed) works on paper (graphic art). The portraits represented various cultural backgrounds from the Western hemisphere and were created by artists from different countries and centuries, employing different techniques (Table 1).

(5) Using the same scanning procedure, calibrated scans were obtained from reproductions of colored portraits (oil paintings) that originated from a cultural

background similar to that of the monochrome portraits. Color images were converted to grayscale using the YIQ transform where luminance is expressed as the sum of the weighted contributions from the RGB channels (relative weights: R, 0.3; G, 0.59; B, 0.11), as previously done in another study of colored art images (Graham and Field 2007).

The scanner was calibrated for gamma gradation with the IT8 target printed on reflective paper (LaserSoft Imaging, Kiel, Germany). The target displayed 24 gray values of measured luminances. A grayscale conversion table was generated that allowed transformation of all monochrome scans to linearized gray scale values. For color scans, the scanner was gamma calibrated with the same target using the SilverFast Ai Professional Scan Software, version 6.5 (LaserSoft Imaging).

The reproductions chosen for analysis were of relatively large size and high quality and displayed works of art with no or only minor defects (paper cuts, stains, folds etc.). In all portraits, faces covered a large part of the image.

The artistic portrait database was analyzed in two different formats. First, as described previously, the scanned images were padded according to square ones by adding a uniform border with a gray value equal to the average gray value in the image (Redies et al. 2007). Examples are shown in Figure 1K-M.

Second, square details of the portraits were generated showing face, neck and shoulders of the portrayed persons at a magnification comparable to that of the photographic face databases (Fig. 1N-P). For normalization, eye distance was measured (front views) or estimated on the basis of the distance between eyes and the mouth (side views).

Image Analysis

Image analysis was carried out using Matlab as described previously (Redies et al. 2007). Briefly, each input image from the test sets of different dimensions was resized to 1024 x 1024 pixels by bicubic interpolation. After transforming each image into the frequency domain using Fast Fourier Transform, the rotational average of the power spectrum was computed for each frequency. Power spectrum (amplitude squared) and frequency were analyzed in the log-log plane (Fig. 2). Next, a least squares fit of a line to the log-log power spectrum was performed by fitting data points that were binned at regular intervals. Only the frequency range between 10 and 256 cycles per image was used for the fitting. This restriction minimized the effect of artefacts in our analysis, for example artefacts due to low pass filtering, rectangular sampling, raster screen or noise in the images. The result for each image is the slope of the line and the deviation of the data points from that line, calculated as the sum of the squares of the deviations of the data points, divided by the number of data points.

In total, we analyzed five different data sets, consisting of natural scenes (208 images), photographic images of faces (Yale face database B, 5776 images; AR face database, 3313 images), monochrome portraits by artists (306 images) and colored oil portraits converted to grayscale values (141 images).

Results

In Figure 2, Fourier spectral power of two representative images from the databases is plotted as a function of spectral frequency. In the log-log plane, the binned data points deviate only slightly from the straight fitted line, within the frequency range analyzed. However, the two fitted lines differ in their slope. The fitted line of the face photograph is steeper (slope of –3.69) than that of the artist's rendering of a human face (slope of –1.84). A slope constant of about –2 (or -1 if spectral amplitude instead of power is plotted) indicates that the image has scale-invariant or fractal-like properties, as previously shown for natural (complex) scenes

(Burton and Moorhead 1987; Field 1987; Olshausen and Field 2004; Ruderman, 1997; Ruderman and Bialek, 1994; Simoncelli and Olshausen 2001; Tolhurst et al. 1992). Close-up views of simple objects generally result in steeper slopes (Bosworth et al. 2006; Redies et al. 2007; Torralba and Oliva 2003).

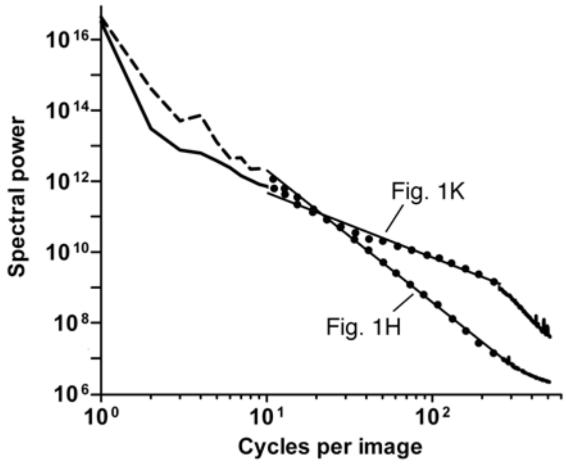

Figure 2. Example of the Fourier spectral analysis. In the log-log plane, Fourier power (amplitude squared) was plotted as a function of spectral frequency. A line was fitted to values that were binned at regular logarithmic intervals between 10 to 256 cycles per image (dots). The dashed and solid lines represent results for the images displayed in Figure 1H and K, respectively. Slopes and deviations from the fitted line are –3.69 and 0.005 (for Fig. 1H) and –1.84 and 0.007 (for Fig. 1K).

Figure 3 shows scatter diagrams with the slope of each image plotted on the X axis and the deviations from the fitted lines plotted on the Y axis, for each of the image datasets analyzed. The majority of images can be fitted well by a straight line, as indicated by the small deviations of the data points from the fitted line.

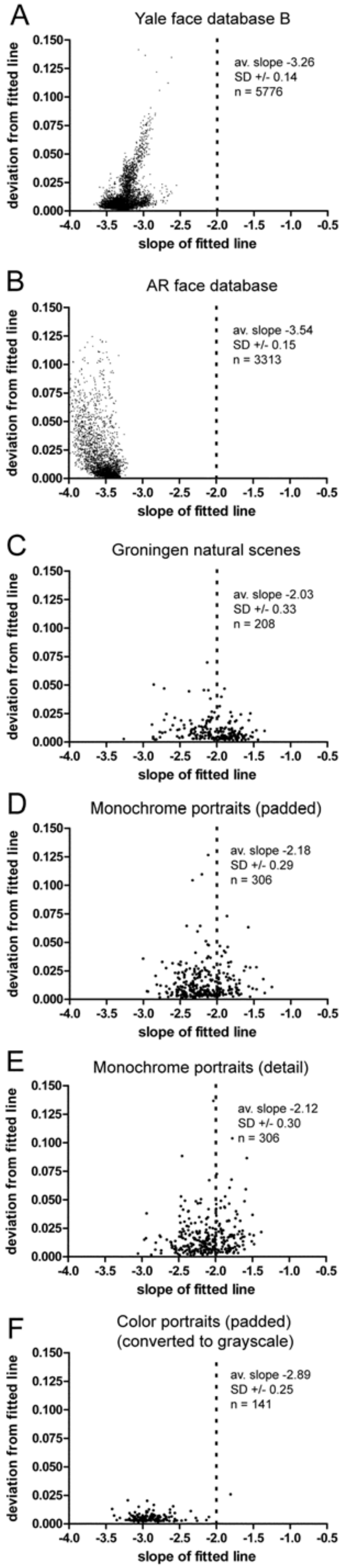

Figure 3. Results of the Fourier spectral analysis. Each dot in the scatter diagrams represents the slope of the fitted line for one image and the deviation of the measured data points from the fitted line for that image. Data shown in C are from Redies et al. (2007). Av. slope, average slope for the set of images.

The average slopes are –3.26 for the Yale face database (Fig. 3A) and –3.54 for the AR face database (Fig. 3B). This difference is probably due to the office background in the Yale face database. After replacing this background by a white background in 30 randomly selected images from the Yale face database, the slope became more negative for all images; the average slope for the 30 images shifted significantly from –3.28 (+/- 0.12 SD) to –3.57 (+/- 0.15 SD; $p<0.0001$, paired t-test).

For natural scenes (Fig. 3C) and monochrome portraits (Fig. 3D), slopes were significantly higher than for the face photographs (-2.03 and -2.18, respectively; non-parametric statistical analysis by Kruskal-Wallis test with Dunn's multiple comparison post-test, $p<0.001$). For color (oil) portraits that were converted to monochrome images, the average slope was –2.89 (Fig. 3F), which is significantly more negative than the slope for natural scenes or monochrome portraits ($p<0.001$) and significantly more positive than the slope for the two face photograph databases ($p<0.001$).

The difference between the slopes of monochrome portraits and face photographs may be due to the fact that, in some of the portraits, faces were viewed from a larger distance and were embedded in complex scenes. As an index of face size in the padded portraits, the eye distance was expressed as a percentage of image dimension. Average eye distance was 19.6% of image dimension (+/- 1.9 SD) in the Yale face database, and 19.7% (+/- 1.4 SD) in the AR face database, compared to 15.5% (+/- 4.6 SD) in the portrait database. Figure 4 shows the dependency of the measured slope constants on the eye distance for the monochrome portraits. The two variables did not significantly correlate with each other (Spearman correlation coefficient r=-0.003). We repeated our analysis for details of the portraits, which were enlarged in size so as to match approximately the size of the photographed faces. For the portrait details (Fig. 1N-P), average eye distance was 20.3% (+/- 5.8 SD). The mean slope for this dataset was –2.12 (+/- 0.30 SD; Fig. 3E), which is close to the average slope of the padded portraits (-2.18; Fig. 3D).

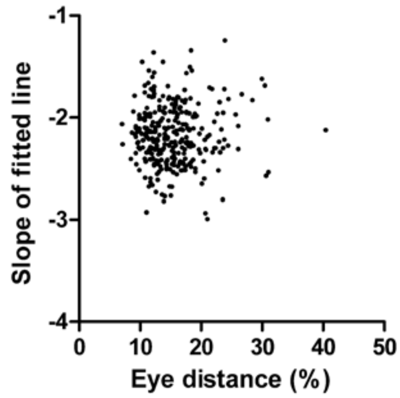

Figure 4. Slope of the fitted lines plotted as a function of eye distance for the 306 padded images of monochrome portraits. Eye distance was expressed in percent of the image dimension.

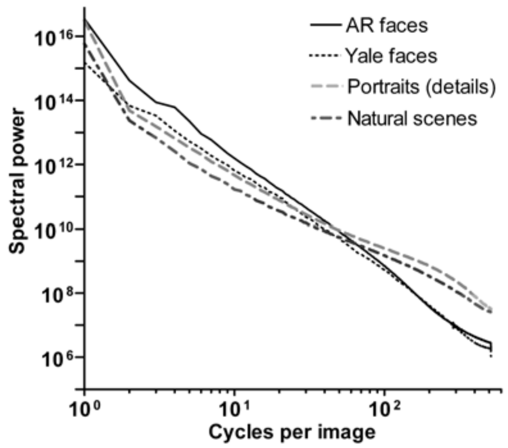

Figure 5. Average curves for the different categories of face images and natural scenes.

For the face details, there were only small or no significant differences in the average slope constants between faces painted on homogeneous versus complex background, between persons portrayed with and without headdress, between faces of children, women, and men with and without beards, or between front views and side views of faces (Table 1). Also, cultural variables, such as techniques, centuries and country of origin had only a small or no significant influence on the slopes (Table 1).

Table 1. Slopes of the fitted line for portraits by artists (details), calculated separately for different cultural and other variables

	Slope (mean ± SD)	n
All	-2.12 ± 0.30	306
Background		
Homogeneous	-2.11 ± 0.29	195
Complex	-2.13 ± 0.31	111
Headdress		
No	-2.11 ± 0.30	188
Yes	-2.13 ± 0.29	118
Gender		
Child	-2.09 ± 0.25	26
Women	-2.14 ± 0.30	46
Man, without beard	-2.10 ± 0.30	145
Man, with beard	-2.13 ± 0.32	89
View		
Front	-2.11 ± 0.30	253
Side	-2.15 ± 0.28	53
Century		
15th Century	-1.95 ± 0.16	20
16th Century	-2.10 ± 0.24	89
17th Century	-2.05 ± 0.36	34
18th Century	-2.18 ± 0.16	18
19th Century	-2.16 ± 0.37	50
20th Century	-2.16 ± 0.32	95
Country		
Italy	-2.14 ± 0.27	57
Flanders	-1.87 ± 0.26	34
France	-2.24 ± 0.37	45
Germany	-2.12 ± 0.26	150
Other countries	-2.14 ± 0.32	20
Techniques		
Etching	-2.04 ± 0.33	50
Engraving	-2.08 ± 0.24	17
Lithograph	-2.20 ± 0.23	27
Woodcut	-2.37 ± 0.44	13
Charcoal, chalk	-2.16 ± 0.26	100
Pencil, silver point	-2.02 ± 0.23	59
Pen drawing	-2.05 ± 0.33	31
Brush drawing	-2.32 ± 0.37	9

Values are means ± standard deviations (SD).
n: number of images analyzed in each category.

In Figure 5, the logarithmic average of all spectral power curves for the different image categories is plotted as a function of spectral frequency in the log-log space. The curves for natural scenes and portraits by artists are more shallow than those for photographs of faces.

The scanner used for digitizing the reproductions of portraits from art books was calibrated for linearized conversion of color and brightness into pixel values (see Methods). However, we cannot control for gamma gradation during reproduction in art books. We therefore asked what effect moderate degrees of gamma gradation have on the slopes measured by us. Figure 6 shows that the effect of gamma values between 0.25 and 4 is minor.

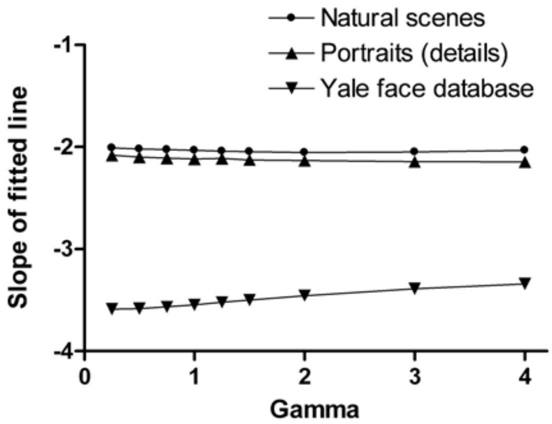

Figure 6. Average slopes of the fitted lines plotted as a function of gamma gradation applied to three different image datasets (Yale face database, natural scenes and details of portraits by artists). From the Yale face database, a subset of 300 randomly selected images were used for the analysis.

Discussion

Methodological considerations

Our analysis reveals that artists endow human faces with image statistical properties similar to those of complex natural scenes (Burton and Moorhead 1987; Field 1987; Olshausen and Field 2004; Ruderman, 1997; Ruderman and Bialek, 1994; Simoncelli and Olshausen 2001; Tolhurst et al. 1992). Before accepting this result, trivial explanations for our findings and experimental artifacts must be excluded. We therefore carried out control experiments, which show that the present result is unlikely to originate in reproduction artefacts and that it cannot be explained by systematic differences in the complexity of the visual patterns surrounding the faces in the portraits.

A number of artefacts might possibly influence the measurements of the slopes in the log-log plots, for example artefacts caused by reproducing art images in books. One such artefact may be non-linearities in the transformation of color and brightness to pixel values during photography, scanning and printing. Such non-linearities are commonly expressed as changes in gamma gradation. Here, we demonstrate that moderate degrees of gamma gradation, which can be anticipated in the reproduction process, have only a minor effect on the values of the slope constant measured in our experiment (Fig. 6). A similar robustness of the slopes has been previously reported in natural scenes for changes in contrast or in gray value offset (for a review, see Ruderman 1997). The effect of other reproduction artefacts has been minimized by restricting the frequency range in the analysis (see Methods). It is therefore unlikely that reproduction artefacts have a major effect on our results. The frequency range restriction may explain why other investigators, who did not restrict the frequencies range, obtained slightly lower values for the slopes (Graham and Field 2007; Tolhurst et al. 1992).

Secondly, the three databases of human faces differ in the complexity of the background shown in the images. Images from the AR Face Database show the face, neck and shoulders of each person on a uniform bright background. Images from the Yale Face Database show similar body parts in front of an office background, resulting in less negative slope values. Images from the art portrait database generated by us depict persons or faces at variable distances and with backgrounds of different degrees of complexity. It is thus possible that the higher slope values reflect a higher complexity of the rest of the image rather than of the face. This possibility, however, was excluded by normalizing the eye distance in the portraits to those of the photographic faces. Moreover, we did not observe any difference in the slopes between faces portrayed on a complex background and faces portrayed on a homogeneous background (Table 1).

Thirdly, artists often portray humans with elaborate accessories, such as fancy hats, which represent complex visual stimuli and may also result in higher slope constants. However, slopes of portraits with and without headdress were not significantly different from each other (Table 1). Also, the absence or presence of beards, which may also induce complexity in the portraits, did not influence the results (Table 1).

A paradoxical shift of image statistics in artists' portraits

Our results suggest that artists have an implicit knowledge of image statistics and tend to shift the statistics of human faces in their portraits toward the fractal-like statistics of complex natural scenes. As a result, artists portray human faces with statistics different from those of face photographs. This paradoxical shift demonstrates that artists do not necessarily strive to represent natural objects as they are in reality. Rather, they follow unspecified rules that call for an implementation of image statistics similar to those of complex natural scenes. A similar conclusion has been reached for biased samples of non-representational (abstract) art, including oil paintings (Redies et al. 2007; Taylor 2002; Taylor et al. 1999).

The present results are in line with previous observations for a large set of graphic art of the Western hemisphere (Redies et al. 2007). This study showed that, on average, graphic art is created by artists with the fractal-like statistics of natural scenes. However, in our previous study, we did not compare the statistics of art images and their natural counterparts and most works of art included in our previous study depicted complex scenes.

Sampling bias and the universality of image statistics in art

The artistic portraits analyzed here represent a biased sample of art images. First, we demonstrate fractal-like properties only for monochrome portraits or portraits, which were washed with thin color and converted to monochrome images. The inclusion of the color dimension in our analysis would have complicated the analysis.

After conversion to monochrome images, fully colored portraits (color oil paintings) show Fourier spectral statistics in between those of photographed faces and natural scenes (Fig. 3F). Color is an important attribute to art and adds to its esthetic appearance. It may thus come as no surprise that the luminance component of color art has different Fourier statistics than that of monochrome art. Graham and Field (2007) recently obtained Fourier statistics similar to natural scenes also for monochrome renderings of color paintings. Their biased sample of art, however, contained complex scenes and was not restricted to portraits, which may explain the difference in the results.

Another bias stems from the fact that we selected works of art from well-known artists that have been preserved in prestigious museums. We assume that the esthetic value of these works of art is an important reason why they have been conserved, in some cases over many centuries. Due to this bias, conclusions about the image statistics of art reached in the present study likely apply only to esthetic forms of art but not to other, contemporary forms of non-esthetic art (see discussion in Redies 2008).

Despite these biases, our sample of graphic art contains representational art from a large variety of different cultural backgrounds within the Western hemisphere and different graphic techniques. As shown previously for a set of Western graphic art, which depicted multiple subject matters and included abstract art (Redies et al. 2007), the dependence of the slopes on the cultural variables is small, if significant at all (Table 1). Similar statistics were found for the abstract drip paintings of Jackson Pollock (Taylor et al. 1999) and in a set of paintings that included a large proportion of art from the Middle East and Asia (Graham and Field 2007). The widespread occurrence of this finding in different forms of art and artistic techniques and in various human cultures is striking, but its universality in all form of esthetic art remains to be established.

Questions and hypotheses

Fractal-like properties may be a general attribute of esthetic visual displays but cannot be a sufficient criterion for esthetic art for several reasons. First, computer-generated artificial images with $1/f^2$ power statistics (Lee and Mumford 1999; Olshausen and Field 2000; Ruderman 1997) do not necessarily look esthetically pleasing. Second, the range of slope values measured for artistic portraits in the present study overlaps extensively with examples of image classes that are little or not at all esthetic (Redies et al. 2007). Third, there is a clear difference in the profoundness of esthetic appeal between art objects and natural scenes; these differences do not correlate with differences in the measured slopes.

If $1/f^2$ power statistics are not sufficient to induce esthetic perception, what is the reason for artists to shift image statistics in portraits? Does this shift provide insight into the sensory principles underlying esthetic perception? In an attempt to address this question, we would like to raise the following two speculative points:

(1) The visual system is adapted to the statistics of complex natural scenes by evolution and development (Field 1987; Hoyer and Hyvärinen 2002; Olshausen and Field 1996; Parraga et al. 2000; Simoncelli and Olshausen 2001; Vinje and Gallant 2000). In turn, artists adapt their creations to functional features intrinsic to the human visual system (Zeki 1999). The present results are compatible with the

hypothesis (Redies 2008) that the functional features, to which artists induce resonance in their visual system, are related, in some unknown way, to the adaptation of the visual system to natural scenes. Following this idea, the $1/f^2$ power statistics discovered in visual art should be thought of as a corollary of other, as of yet unidentified, principles of esthetic perception. Artists may not be able to express these statistical principles in precise, every-day language (Redies 2008). For example, Fourier analysis can hardly be carried out in the conscious human mind. Indeed, Fourier analysis is a scientific concept that most artists cannot have been aware of until the 20th century.

(2) Alternatively, it may be argued that artists often aim to convey or emphasize particular traits of their subjects (for example, personality traits or expressed emotions). To achieve this goal in the artistic portraits, artists might use specific artistic techniques (for example, sketching with lines or fine textures) that carry more energy in the higher frequency range. However, in art images depicting complex (natural) scenes with similar techniques, the frequency spectra of the depicted scenes did not change on average (Redies et al., 2007). Therefore, graphic art is not generally associated with an increase in higher frequencies. Moreover, as discussed above, other artistic techniques result also in art images with scale-invariant properties.

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