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Minireview

Statistical regularities in art: Relations with visual coding and perception

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ABSTRACT

Since at least 1935, vision researchers have used art stimuli to test human response to complex scenes. This is sensible given the "inherent interestingness" of art and its relation to the natural visual world. The use of art stimuli has remained popular, especially in eye tracking studies. Moreover, stimuli in common use by vision scientists are inspired by the work of famous artists (e.g., Mondrians). Artworks are also popular in vision science as illustrations of a host of visual phenomena, such as depth cues and surface properties. However, until recently, there has been scant consideration of the spatial, luminance, and color statistics of artwork, and even less study of ways that regularities in such statistics could affect visual processing. Furthermore, the relationship between regularities in art images and those in natural scenes has received little or no attention. In the past few years, there has been a concerted effort to study statistical regularities in art as they relate to neural coding and visual perception, and art stimuli have begun to be studied in rigorous ways, as natural scenes have been. In this minireview, we summarize quantitative studies of links between regular statistics in artwork and processing in the visual stream. The results of these studies suggest that art is especially germane to understanding human visual coding and perception, and it therefore warrants wider study.

1. Introduction

Since art is designed for viewing by other humans, it is especially germane to vision science. Art represents a special class of images, and the analysis of visual art may be useful for understanding human vision. A similar proposal has been made for natural scenes. Over the past 20 years of natural scene research, it has become clear that natural scenes represent only a tiny fraction of all possible images and they contain a wealth of regular statistical structure. Notably, natural scenes contain higher-order redundancy not captured by most artificial stimuli (for a review, see Simoncelli & Olshausen, 2001). Recent research has demonstrated that the structure of natural scenes affects visual coding strategies in vertebrates and invertebrates. In other words, the visual system has adapted in evolution and ontogeny to efficiently process the natural scenes that surround individual organisms, through both shared and species-specific strategies. Visual art, in turn, is created through feedback with the artist's visual system, so that art images can be adapted to functions of human vision. Consequently, the study of art images and natural scenes—and relationships between the two—may result in important insights into the biology of the visual system.

In the present review, we will focus on regularities of spatial, luminance, and color statistics in art images. The central tenet of the present review is that regularities in art relate to basic functions of human perception. A host of studies through the history of modern vision science have employed art stimuli to study human visual system response (e.g., Buswell, 1935; Wooding, Mugglestone, Purdy, & Gale, 2002; Yarbus, 1967), perhaps because of the "inherent interestingness" (Hochberg, 1978) of such images. However, these studies have generally ignored the statistical regularities of such stimuli. The present paper is intended in part as an initial guide to these regularities.

The review is divided into two parts. First, we describe statistical regularities in artwork that appear related to low-level processing strategies in human vision, in particular to the processing of natural scenes (Section 2 – Part 1). Second, we describe variations in these statistics and how they have been tied to perceptual judgments and used to discriminate between different styles of art (Section 3 – Part 2).

2. Part 1. Statistical regularities in art

2.1. Pairwise spatial statistics

Converging evidence demonstrates that artworks show statistical regularities. A particular focus of recent research, mostly from our own groups, is the study of the Fourier spatial frequency power (or amplitude) spectra of visual art, which are equivalent to the pairwise (second-order) correlation statistics. Examples for the

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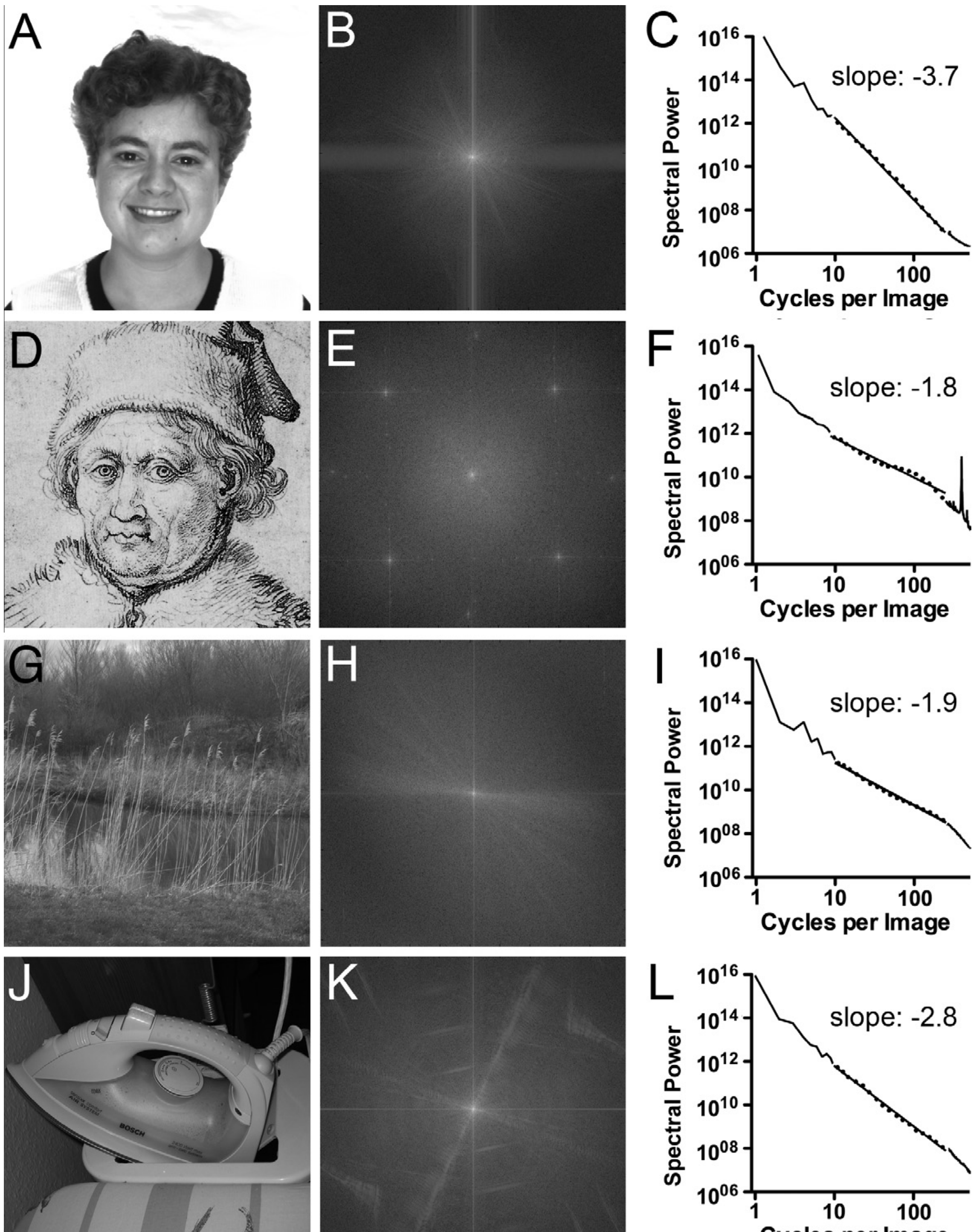

Fig. 1. (A) Original images (A, D, G, J), their Fourier power spectra (B, E, H, K) and log–log plots of radially averaged Fourier power versus spatial frequency (C, F, I, L). A–C. Example from the AR database of face photographs (Martinez & Benavente, 1998). D–F. Portrait (engraving) by the 15th century artist Martin Schongauer. G–I. Example from the Groningen database of natural scenes (Van Hateren & van der Schaaf, 1998). J–L. Photograph of a simple object (Redies, Hasenstein et al., 2007). In the Fourier spectra (B, E, H, K), the low spatial frequencies are represented at the center and lighter shades represent higher power. In the log–log plots (C, F, I, L), straight lines are fitted to binned data points between 10 and 256 cycles/image (Redies, Hänisch et al., 2007; Redies, Hasenstein et al., 2007). The slope of the line is given in each panel (see Table 1 for average values of each image category). The image shown in D is reproduced with permission from "Das Berliner Kupferstichkabinett", Akademischer Verlag, Berlin, 1994 (inventory number: 916-2; © Staatliche Museen zu Berlin, Kupferstichkabinett). The other images are reproduced with permission from the authors.

Fourier spectra of different categories of images are shown in Fig. 1B,E,H,K). The power spectrum measures the relative contribution of different spatial frequencies to the image as a whole. Evidence from neurophysiological studies suggests that the visual system contains frequency-specific response elements that perform a similar analysis at early stages of information processing (DeValois & DeValois, 1980).

In independent studies, Graham and Field (2007, 2008a), Redies, Hänisch, Blickhan, and Denzler (2007) and Redies, Hasenstein, and Denzler (2007) observed that, on average, the Fourier spectral

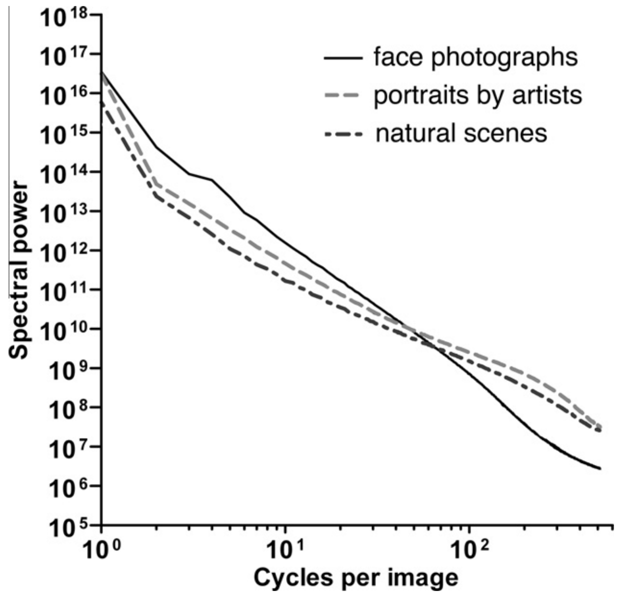

Fig. 2. Log–log plots of radially averaged Fourier power versus spatial frequency. Average curves are given for the datasets of face photographs (AR face database; Martinez & Benavente, 1998), for 200 examples from the Groningen natural scene database (Van Hateren & van der Schaaf, 1998) and for 306 monochrome art portraits of Western provenance. Note that the average curves for the art portraits and natural scenes have a similar slope and are more shallow than the average curve for the face photographs (see also Table 1). Data modified after Redies, Hänisch et al. (2007).

Table 1
Slope value ($-p$) for log–log plots of radially averaged Fourier power versus spatial frequency for different categories of natural and artistic images.

	$-p$	SD[a]	n[b]
Natural scenes[c,d]	−2.0	0.3	208
Photographs of plants[c]	−2.9	0.4	206
Photographs of simple objects[c]	−2.8	0.3	179
Photographs of faces[e,f]	−3.5	0.2	3313
Graphic art of Western provenance[c]	−2.1	0.3	200
Artistic portraits (graphic art)[e]	−2.1	0.3	306
15th century	−2.0	0.2	20
16th century	−2.1	0.2	89
17th century	−2.1	0.4	34
18th century	−2.2	0.1	18
19th century	−2.2	0.4	50
20th century	−2.2	0.3	95
Etching	−2.0	0.3	50
Engraving	−2.1	0.2	17
Lithograph	−2.2	0.2	27
Woodcut	−2.4	0.4	13
Charcoal, chalk	−2.2	0.3	100
Pencil, silver point	−2.0	0.2	59
Pen drawing	−2.1	0.3	31
Scientific illustrations[c]	−1.6	0.3	209

[a] Standard deviation.
[b] Number of images in each category.
[c] Data from the study by Redies, Hasenstein et al. (2007).
[d] Images from the database of van Hateren and van der Schaaf (1998).
[e] Data from the study by Redies, Hänisch et al. (2007).
[f] AR face database of Martinez and Benavente (1998).

power of art images tends to fall with spatial frequency according to a power law $1/f^p$, where p is about 2 (Figs. 1D–F and 2; Table 1). This result implies that the power spectra of art images are roughly scale-invariant (i.e., fractal-like). Scale-invariance can be visualized if radially averaged Fourier power is plotted as a function of spatial frequency in the log–log domain (Figs. 1C,F,I,L and 2). Typically, spectral power in such plots falls linearly for most images; the slope of the curve corresponds to $-p$ in the above term. For scale-invariant images, the slope of the curve has a value of −2 (or −1, if amplitude is plotted instead of power).

It is well established that natural scenes are another image category that, on average, displays rough scale invariance (Fig. 1G–I and Table 1; Burton & Moorhead, 1987; Field, 1987; Tolhurst, Tadmor, & Chao, 1992). Due to the structure of natural scenes (Field & Brady, 1997; Ruderman, 1997), which manifests itself across a wide range of different scales, the relative power of low and high spatial frequencies in the Fourier statistical properties changes little when one zooms in and out of the images, within a range of scales. Other categories of images, like photographs of plants or parts of plants, and photographs of objects or human faces, have significantly lower slope values that range between −2.5 and −3.5 (Figs. 1A–C,J–L and 2; Table 1; Redies, Hänisch et al., 2007; Redies, Hasenstein et al., 2007; Torralba & Oliva, 2003).

Despite relatively minor differences in the slope values, which may depend on the sampling strategy for the different types of art images, our independent results have established that rough scale-invariance is a rather universal property of visual art in different cultures and art styles. Redies, Hänisch et al. (2007), Redies, Hasenstein et al. (2007) analyzed several hundred works of art that represent a wide variety of monochrome (mostly grayscale) graphic art of Western provenance from different artists, countries, centuries (15–20th), subject matters (landscape, portrait, abstract, etc.), and techniques (etchings, woodcuts, drawings, etc.). The differences in the measured slope values for the different image variables were relatively small, if significant at all, compared to the differences in images of non-complex objects (Table 1). For example, lithographs are generally composed more coarsely and have slope values of around −2.2 to −2.3 while engravings are typically composed of thin lines and have slightly lower slope values around −2.1. The studies by Graham and Field (2007, 2008a) also detected approximately scale-invariant statistical properties in 124 paintings from an art museum, representing a roughly equal share of paintings from the Western and Eastern hemispheres. Moreover, abstract art appears to show similar structure as well (Graham & Field, 2008a; Redies, Hasenstein et al., 2007). While images lacking such scaling can be considered fine art—e.g., monochromes, or works with power at only one spatial frequency, e.g., Agnes Martin's grid paintings—such examples are rare. Moreover, these results mirror the finding of $1/f$ structure in music (Beauvois, 2007; Dagdug, Alvarez-Ramirez, Lopez, Moreno, & Hernandez-Lemus, 2007; Voss & Clarke, 1975).

These results generalize earlier findings by Taylor and colleagues who focused on the work of the American 20th century artist Jackson Pollock. Using a box-counting measure (which is mathematically identical to the spatial frequency power spectrum; see Knill, Field, & Kersten, 1990). Taylor, Micolich, and Jonas (1999) and Taylor et al. (2007) showed that the paint layer outlines of Pollock abstract drip paintings display fractal-like scaling. This finding has generally been supported by evidence from Alvarez-Ramirez, Ibarra-Valdez, Rodriguez, and Dagdug (2008) and Mureika, Dyer, and Cupchik (2005), though some of Taylor's analyses have been refuted by Jones-Smith and Mathur (2006).

Because many natural scenes depicted by artists show similar proportions of large-scale structure and fine detail compared to the scenes themselves, the usage of natural scene statistics in artwork may be interpreted as an imitation of these statistics. However, Redies, Hänisch et al. (2007) compared photographs of human faces with artistic portraits of human faces. Surprisingly, they found that artists portray human faces with the Fourier characteristics of natural scenes (slope values around −2) rather than with those of real faces (slope values of around −3) (Figs. 1 and 2; Table 1). This result suggests that artists do not merely imitate the statistics of the real world, but could have a preference for the usage of specific image statistics in their work.

Taken together, these results suggest an influence of early visual coding strategies in the production of art. Viewed from one perspective, this influence is manifest in the fact that art, on average, possesses the same correlation structure as natural scenes, suggesting that artists produce works generally suited for a visual system already adapted to these statistics (the difficulty of making images by hand without this structure also contributes to this regularity; see Graham & Field, 2008a). Viewed another way, artist-imposed regularities in the power spectrum could in part contribute to aesthetic perception—particularly for faces—because of the statistical match with natural scenes (Section 3.1; Redies, 2007).

2.2. Sparseness

Statistical sparseness has emerged as an important basic regularity in natural scenes, which is reflected in sparse-distributed neural coding strategies (for reviews, see Graham & Field, 2006; Simoncelli & Olshausen, 2001). There is evidence that art also shows sparse structure. Artists appear to approximate the sparse statistics of natural scenes once the luminance range of scenes has been compressed to match that of art. In particular, though simulated retinal and cortical representations of natural scenes show higher sparseness than those for artworks, artworks show higher sparseness in these representations when images are transformed by a photoreceptor-like luminance nonlinearity (Graham & Field, 2007).

Sparseness may also relate to higher-level properties of art. As noted in Section 3.2, sparse coding models have recently been demonstrated to outperform other image representations (e.g., wavelets and curvelets) in performing stylistic classifications (Hughes, Graham, & Rockmore, 2010). It has been suggested that sparse coding succeeds in this case because it captures local spatial features characteristic to an artist. In addition, sparseness of intensity distributions has been shown to correlate with similarity judgments of art (see Section 3.3).

2.3. Luminance

As noted above, luminance statistics in art differ in fundamental ways from those of natural scenes due to the optical properties and illumination of paintings (Graham & Field, 2007, 2008a): artwork shows a much smaller dynamic range of luminances than is encountered in natural scenes. Moreover, given that natural scene luminance distributions are typically highly skewed and roughly log–normal, and given that artists generally use non-linear transforms to represent scene luminances (Graham & Field, 2008b; Graham, Friedenberg, & Rockmore, 2009) the result is that luminance distributions in artwork are less skewed compared to natural scenes (Graham & Field, 2007, 2008b). Considering that photoreceptors also overcome dynamic range restrictions by performing non-linear scaling, luminance transforms in art may be effective for many of the same reasons that a log-like nonlinearity is useful at the photoreceptor level, though it may not be a result of photoreceptor luminance compression.

2.4. Color

Color is certainly a crucial aspect of art but we note that to date, only a handful of studies have examined the role of color statistics in art perception (e.g., Wallraven et al., 2009, discussed below). Notably, Pinto, Linhares, Carvalhal, and Nascimento (2006) manipulated color statistics of hyperspectral images of Renaissance paintings to determine lighting conditions that viewers consider optimal. They found that the increased chromatic diversity generated by illuminants was an important factor in human preference. Related work has been attempted by Mureika (2005). Large-scale studies of the relationship between color statistics in art and natural scenes are still missing to date. We speculate that future work on colored art images will also show similarities to the coding of natural scenes, given that relationships between natural color statistics and color processing in the human visual system have been described (see e.g., Foster, Amano, & Nascimento, 2006; Ruderman, Cronin, & Chiao, 1998; Webster & Mollon, 1997).

2.5. Composition-level statistics

A number of studies have examined statistical properties of art beyond the basic image statistics described above. Here, we give only some examples of such statistics, which relate to gross properties of composition. A complete survey of composition-level statistics is beyond the scope of the present review (see, e.g., Tyler, 2007).

Cheyne, Meschino, and Smilek (2009) found consistent variations in the relationships among marks in Paleolithic cave painting. In this innovative study, statistical relationships between anatomical features in animals and their painted representation were evaluated. Results suggest that these variations are a form of caricature, and that they therefore stand as evidence of human perception of typicality and categorization. The authors propose that cave artists were keen observers of the wildlife they painted (cf. Guthrie, 2005), and that individual variations in composition reflected the deep knowledge of these animals that contemporary viewers would readily understand. This result relates to the proposal of Ramachandran and Hirstein (1999), who argued that representational art in many cultures is largely directed towards identifying and exaggerating distinctive features in the manner of caricature. These authors see art as an aesthetic manifestation of the "peak-shift effect," wherein animals (particularly the young) respond more favorably to exaggerated, counterfeit versions of relevant stimuli than to "natural" versions of those same stimuli.

More basic compositional statistics have also been measured. Tyler (1998) found that portraiture through many eras and cultures tends to center one or the other eye along the vertical center of the canvas. A similar idea has been proposed by Schirillo (2000), who used behavioral tests to examine asymmetries in the direction in which portrait sitters are oriented. Schirillo suggests the orientation of faces in Rembrandt portraits is related to emotional cues via an effect of hemispheric asymmetry.

3. Part 2. Statistical regularities and visual perception

3.1. Aesthetics

Experimental psychology has long taken an interest in aesthetics. In his landmark "Vorschule der Ästhetik" ("Preschool of Aesthetics"; 1876), Fechner (1876) advocated a "bottom-up aesthetics" aimed at deducing aesthetic principles from empirical observations and he called for a systematic statistical analysis of aesthetic preferences by humans. In Fechner's time, this approach was highly innovative and contrasted with the "top-down aesthetics" of philosophers who deduced aesthetic principles from a system of general truth or from divinity. To test his idea, Fechner studied the aesthetics of the golden ratio, which was claimed to be inherently more aesthetic than other ratios. For a rectangle, its two sides are in the golden ratio (also called phi = 1.618 ...) if the ratio between the sum of the two sides and the longer side is the same as the ratio between the longer side and the shorter side. Especially since the Renaissance, the golden ratio has been used in particular types of architecture and artworks throughout the

Western hemisphere (but see Markovsky, 1992). However, several modern psychological studies rejected the proposition that ratios close to the golden ratio are preferred by human observers (see, e.g., Boselie, 1984; McManus, 1980; Russell, 2000). It is clear, though, that the golden section and related numbers, for example the Fibonacci series, have biological significance, especially for growth patterns, optimal construction, maximally dense spacing and energy minimization. As a consequence, many natural patterns are composed of elements with proportions or numbers that correspond to the golden ratio (for example, for phyllotaxis, see Mitchison, 1977).

Although Fechner's measurements of the aesthetics of the golden ratio did not stand the test of time, his thinking has influenced the study of aesthetics up to the present time, in particular, in approaches that apply information theory to aesthetics. Birkhoff (1933) defined a simple aesthetic measure as the ratio between order and complexity. In his theory, order depends on the geometrical relations (for example, harmony, symmetry or balance) among segments of a perceived image, and on the complexity in the number of regions of interest in the image that attract the viewer's attention. Following Birkhoff, other theories that combined aesthetics with information theory included the work by Bense (1969) and Arnheim (1971). More recently, these ideas were supplemented by explorations of Kolmogorov complexity and Zurek's physical entropy for pixel values in paintings by Mondrian, Pollock, and Van Gogh (Rigau, Feixas, & Sbert, 2008). Although these attempts have all considered that the human observer and the artist play a crucial role in the process of artistic appreciation and creation, they wrongly invoke information theory in a situation where the "symbols" that constitute aesthetic stimuli (and natural images more generally) are unknown. Indeed, the "true" entropy of an image is a perceptual quantity, and cannot therefore be characterized with image statistics (e.g., Shannon information) alone (see Kersten, 1987; Chandler & Field, 2007). The question of what contributes to aesthetic judgments remains controversial to the present day.

Some have argued that fractal-like patterns are inherently more aesthetic than non-fractal patterns because they resemble natural patterns. This idea has also been advanced in the "savanna hypothesis" by Orians (1986), which proposed that humans have an innate aesthetic preference for stimuli that depict the typical environment, in which the human species evolved. Work by other researchers has elaborated on this approach. Aks and Sprott (1996) reported a preference for artificial fractal patterns with a box-counting dimension of approximately 1.3. Spehar, Clifford, Newell, and Taylor (2003) examined three categories of images (natural scenes, mathematical fractals, and sections of paintings by Pollock) and found a consistent preference for box-counting dimension around 1.3–1.5 for all three image categories. Similar results were obtained by Hagerhall, Purcell, and Taylor (2004) for landscape silhouettes. However, it should be noted that mathematical fractals are not only scale invariant but also self-similar. While the Fourier spectra of natural scenes are indeed scale-invariant, not all natural scenes are self-similar.[1] As a result, we suggest that fractal analysis (especially of binary boundaries) may be more limited than is Fourier analysis for understanding general relations between spatial statistics of natural scenes and the sensory coding of aesthetic stimuli.

What is the relation between $1/f^2$ characteristics in the special case of art stimuli that are aesthetic (see above)? Scale-invariant patterns can be generated that are not necessarily aesthetic (Lee & Mumford, 1999; Olshausen & Field, 2000; Ruderman, 1997), nor is noise with $1/f^2$ characteristics. It is thus clear that $1/f^2$ characteristics are not sufficient to induce aesthetic perception (Redies, Hänisch et al., 2007). $1/f^2$ characteristics may not even be necessary to induce aesthetic perception. Fractal-like scaling should thus be considered a corollary of aesthetic production, rather than the basis of aesthetic judgment. Nevertheless, the finding that portraitists shift the inherent statistics of faces to be more like those of typical natural scenes (see above, Redies, Hänisch et al., 2007) suggests that fractal-like statistics could play a role in aesthetic perception.

We note that a number of researchers have examined other statistical aspects of aesthetics using realistic scenes. Palmer, Gardner, and Wickens (2008) have studied relationships between aesthetic quality and the centering and facing direction of objects in natural and artificial images. Datta, Joshi, Li, and Wang (2006) collected a highly comprehensive set of image statistics and features, as well as semantic data, for user-contributed images on their massive Alipr database, and attempted to model human aesthetics ratings. By using a model that employed support vector machines and classification trees on these statistics, they were able to achieve 70% accuracy (post hoc) in predicting aesthetics ratings.

3.2. Artistic style

In addition to regularities that are shared across human art making, work by individual artists and from different movements in art shows predictable statistical properties. In recent years, researchers have used image statistics to address questions of attribution and style in art, an area termed "stylometry," which is a relative of the larger effort to quantify style in literature (e.g., using word frequency tests and other statistical tools; see Mosteller & Wallace, 1964). Stylometry of art was initiated in its modern form in Van Dantzig's (1973) attempts to classify different types of brush strokes. Digital methods, such as those described below, proceed in a similar spirit.

Work by Taylor and colleagues attempted to provide authentication to newly discovered works thought to be by Jackson Pollock. Taylor et al. (2007) used box-counting statistics of paint splatter outlines in Pollock drip paintings as their metric. After determining a characteristic value of the box-counting dimension for known Pollock works across his drip painting period, which was found to increase monotonically over time, this group found that values for the unknown works deviated significantly from those characteristic of the years in which the unknowns were believed to have been painted. However, a single statistical measure such as box-dimension appears insufficient for providing reliable attribution (see Irfan & Stork, 2009).[2]

In contrast, Wallraven and colleagues (Spehr, Wallraven, & Fleming, 2009; Wallraven et al., 2009) have shown that simple computations based on image color statistics, spatial statistics, and other varieties of image features, are quite able to separate art of different eras. This work is important because it considers a wide range of image features: high-level features (e.g., face detection), mid-level structure (segmentation) and basic image statistics (including color statistics) are employed to achieve clustering by style. Approaches that employ lower level statistical features in combination with more advanced classification methods (Barnard, Duygulu, & Forsyth, 2001; Keren, 2002; Li & Wang, 2004; van den Herik & Postma, 2000; Widjaja, Leow, & Wu, 2003) have also found success in separating paintings by different artists and from different eras (simpler methods also show some success: e.g., Lombardi, Cha, & Tappert, 2005). There is much room for improvement of

[1] As Elkins (2008) has pointed out, it is very difficult for humans to draw or paint fractals (i.e., self-similar patterns) by hand, and therefore such works are extremely rare.

[2] This is an especially grave problem when social and economic interests of the scale associated with Pollock hinge on the outcome of such pronouncements (see Landau & Cernuschi, 2007).

these techniques, and future work will no doubt examine ways of optimizing the weighting of various features for different tasks.

Statistical stylometric measures are most appropriate when classification tasks are well defined and properly circumscribed. For example, Lyu, Rockmore, and Farid (2004) showed that wavelet response statistics are sufficient to reliably separate drawings by Pieter Bruegel the Elder from those by his known imitators (see also Rockmore & Leibon, 2007). In this case, the drawings by contemporaneous imitators employed the same medium, and often depicted the same subject matter as the Bruegels. Therefore, subtle differences in technique can be measured using local spatial statistics of the array of marks. In further work, Hughes et al. (2010) replicated the Bruegel result using an efficient coding model, sparse coding (Olshausen & Field, 1996), and showed that this method produces better classification performance compared to other sparse bases such as wavelets and curvelets. Since sparse coding exploits regularities in higher-order spatial statistics, this result implies that higher-order statistics (as opposed to second-order statistics such as the power spectrum) may be important in human perception of stylistic distinctions.

Image processing tools have also been used to quantify dimensions of variation in paint strokes associated with different artists and styles (e.g., Lettner & Sablatnig, 2008). A recurring challenge in this work is to separate strokes from structure, i.e., to distinguish inherent variations in marks from those related to objects. This challenge is part of the more general problem in computer vision of separating style and content (see Tenenbaum & Freeman, 2000). Since sophisticated models designed to classify art such as those of Wallraven and collaborators yet confound style and content on occasion, there is clearly a need for further research, which will benefit both the vision science and computer vision communities.

Finally, we note that some authors (e.g., Chatterjee, 2006; Lanthony, 2006; Livingstone & Conway, 2004; Marmor & Ravin, 1997) have attempted to relate specific artists' styles to visual system dysfunctions and others have described changes in style after brain injury (Sacks, 1995; Zaidel, 2005). For example, aspects of Monet's style have been attributed to cataracts. Though it is beyond the scope of this review to discuss the wealth of work in this area, and while some of these proposals have been supported by strong evidence (Marmor, 2006), it is important to bear in mind the el Greco fallacy, which is the false notion that artists portray the world as it appears to them (el Greco's elongated figures having been wrongly attributed to astigmatism). Since the image an artist creates also passes through the artist's visual system, it will be subject to the same optical distortions as those that putatively cause distortions in the image (see e.g., Anstis, 2002). Therefore, care must be taken when interpreting art in light of evidence of statistical regularities.

3.3. Affect and perceptual judgment

The relationship between second-order image statistics and affect in abstract art has recently received attention. Work by Fernandez and Wilkins (2008) suggests that observers do not favor abstract art that deviates from natural spatial statistics. Through a suite of studies, these investigators found that abstract art that is statistically abnormal in terms of spatial frequency power made observers uncomfortable. They suggested that this aversion may be related to stimuli that can induce seizure and migraine in people susceptible to these conditions. This finding is consistent with the notion that perception (e.g., discrimination) of stimuli such as white noise is difficult because the visual system is not designed to encode these stimuli. The finding of a link with aversion shows that certain unnatural statistics may be more problematic for the visual system than others.

In addition to work on affect, the idea that basic statistics in art could be related to variations in basic perceptual judgments has been investigated (Graham, Friedenberg, Rockmore, & Field, 2010; Graham et al., 2009). Evidence supports the notion that statistical regularities of natural scenes (such as power spectrum shape) could in principle be extracted by the early visual system to aid perception (Torralba & Oliva, 2003). It has been suggested that for art, pixel sparseness is likewise informative. Experiments have compared the principal components of observers' similarity ratings for paintings to a host of statistical measures, modeled neural responses, and semantic variables derived from image metadata (Graham, Friedenberg, Rockmore et al., 2010). For both landscapes and portraits, it was found that one of the first two similarity dimensions was highly correlated with a measure of intensity distribution sparseness. For abstract art, nearly a third of the variance of similarity ratings could be explained using two basic statistics: the power spectrum slope and the activity fraction (Graham et al., 2009). In studies of preference ratings, these same statistics were found to explain up to a quarter of data variance for landscapes and abstract art (Graham, Friedenberg, McCandless, & Rockmore, 2010). These results can be viewed as evidence that early visual processing could exploit both power spectrum statistics and sparse statistics to perform basic perceptual judgments.

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