Research Article

Journal of the Optical Society of America A

OPTICS, IMAGE SCIENCE, AND VISION

Statistics of colors in paintings and natural scenes

Cristina Montagner,[1,2,*] João M. M. Linhares,[3] Márcia Vilarigues,[1,4] and Sérgio M. C. Nascimento[3]

[1]Department of Conservation and Restoration, Faculdade de Ciências e Tecnologia, Universidade NOVA de Lisboa, Lisbon, Portugal
[2]REQUIMTE-CQFB-Faculdade de Ciências e Tecnologia, Universidade NOVA de Lisboa, Lisbon, Portugal
[3]Centre of Physics, Campus de Gualtar, University of Minho, 4710-057 Braga, Portugal
[4]VICARTE-Faculdade de Ciências e Tecnologia, Universidade NOVA de Lisboa, Lisbon, Portugal
*Corresponding author: montagnercristina@gmail.com

Received 7 October 2015; revised 9 December 2015; accepted 10 December 2015; posted 24 December 2015 (Doc. ID 251526); published 5 February 2016

Painters reproduce some spatial statistical regularities of natural scenes. To what extent they replicate their color statistics is an open question. We investigated this question by analyzing the colors of 50 natural scenes of rural and urban environments and 44 paintings with abstract and figurative compositions. The analysis was carried out using hyperspectral imaging data from both sets and focused on the gamut and distribution of colors in the CIELAB space. The results showed that paintings, like natural scenes, have gamuts with elongated shapes in the yellow–blue direction but more tilted to the red direction. It was also found that the fraction of discernible colors, expressed as a function of the number of occurrences in the scene or painting, is well described by power laws. These have similar distribution of slopes in a log–log scale for paintings and natural scenes. These features are observed in both abstract and figurative compositions. These results suggest that the underlying chromatic structure of artistic compositions generally follows the main statistical features of the natural environment.

OCIS codes: (330.1720) Color vision; (330.1710) Color, measurement.

http://dx.doi.org/10.1364/JOSAA.33.00A170

1. INTRODUCTION

Spatial, spectral, and chromatic properties of natural scenes have been studied for various purposes, for example, to investigate how the spatial properties of the visual system match the natural environment [1–5], the spectral redundancy of natural reflectance functions [6,7], and the efficiency of their visual representation [8]. These studies show that spatial and spectral regularities of nature correlate with human neural coding [9,10]. In the color domain, similar approaches have given useful information, for example, in the estimation of the color distributions characteristic of natural scenes [11,12] and of the number of discernible colors perceived by humans [13], in the assessment of the frequency of natural metamers [14] and of luminance and chromatic edges [15], or in the estimation of the spatial distribution of the color of the illumination [16]. These studies have shown that natural colors show many regularities and are considerably constrained.

Comparative studies of the properties of natural scenes and paintings may help in understanding the relationships between the visual neural mechanism and art, in the same way other studies try to clarify how the visual mechanism influences the decision of the artists' creative practices (see, e.g., [17–22]). Visual aesthetics is mainly determined cognitively but the physical properties of the artworks may give insights to the artistic process [23].

Natural scenes and paintings seem to share important statistical regularities [24,25]. For example, similarly to what happens in natural images, art images are roughly scale-invariant [25]. Features in the paintings of American artist Jackson Pollock revealed a scale-invariant structure that reflects the natural visual statistics [26]. In a study with 124 images of works from the Herbert F. Johnson Museum of Art (Cornell University) and 137 images of natural scenes, similar frequency amplitude spectra were found [24]. Analogous results were obtained by the analysis of 200 monochrome (gray scale) graphic works of art from Western cultures from the 15th century to the 20th century and 208 images of natural scenes [25]. The measure of the energy at different spatial scales was also used to predict the discomfort in images of art and nature [27].

Why do artists reproduce in their works spatial statistical properties characteristic of natural images? A hypothesis is that the artists reproduce statistical regularities to which the human visual system is efficiently adapted [21]. In that way the artist creates a kind of state of "aesthetic resonance" between his or her work and the visual system of the viewer [28].

The chromatic domain is also important, and the relevance of color in the artistic process is well known [19,29,30]. The compositions may be determined by aesthetic and symbolic aspects but also by physical factors, like the palette of pigments and dyes available. Chromatic properties were used to investigate the color palettes in van Gogh paintings [31] and as additional information to support authentication studies [32]. The palette of colors of a set of digital images of the Dutch artist were visualized in RGB and HVS color spaces. The analysis of a set of parameters based on entropy revealed an enrichment of the chromaticity and contrast in the later works of his career [33]. Hyperspectral data were used to create maps of pigment distribution in van Gogh's paintings [34]. Statistical studies of the colors of paintings were also carried out to evaluate some aspects of the color rendering of paintings [35] and to estimate aesthetic [36–38] and emotional [39] responses. Edge features, including color and texture, were used to discriminate paintings from photographs [40,41].

In spite of these studies, there is little data comparing the chromatic properties of natural scenes with those of paintings. To what extent painters replicate the color properties of natural environments is an open question. In this work we addressed this question by analyzing comparatively the colors of 50 natural scenes of rural and urban environments and 44 paintings with abstract and figurative compositions from different authors and epochs. The analysis was carried out using hyperspectral data from both sets and focused on the gamut and distribution of colors in the CIELAB color space.

2. METHODS

A. Hyperspectral Imaging

Hyperspectral imaging data were obtained from natural scenes and paintings with a system developed in-house. Detailed description of the system and acquisition methodologies is given elsewhere for paintings [42] and natural scenes [14]. Briefly, a spectral scan from 400 nm to 720 nm, every 10 nm, was carried out with a fast-tunable liquid-crystal filter coupled with a digital camera. The spatial resolution of the camera was 1344 pixels × 1024 pixels and the field of view was approximately 6.9° × 5.3°. Hyperspectral data were calibrated using the spectrum of the light reflected from a gray reference surface placed in the scene. The reference was a flat surface painted with Munsell N7 matte emulsion paint. The estimate of the spectral reflectance of each pixel of the image was obtained after corrections for dark noise, spatial nonuniformities, and stray light. The spectral radiance from each pixel was then computed from the corresponding spectral reflectance assuming the standard illuminant CIE D_{65} [43]. The spectral accuracy of the hyperspectral imaging in recovering spectral reflectance factors of colored samples is within 2% [14,44].

1. Natural Scenes

The 50 natural scenes analyzed were acquired in the Minho region of Portugal. The scenes were of rural and urban environments and contained both close-ups and distant views. Rural scenes contained natural elements such as dark terrain, trees, grass, ferns, flowers, rocks, and stones, and urban scenes contained buildings and painted surfaces. Detailed description of the database is given elsewhere [13,14].

2. Paintings

Twenty-four of the paintings analyzed belong to the collection of the Center of Modern Art of Calouste Gulbenkian Foundation (CAM-FCG) in Lisbon and were realized by the modernist Portuguese artist Amadeo de Souza-Cardoso between 1911 and 1917 (Fig. 1). Amadeo de Souza-Cardoso was extensively studied in previously works and the analysis of the materials and techniques revealed that the color is one of the most important features of his paintings [45,46]. The other 20 paintings belong to the collection of the Museu Nogueira da Silva in Braga. The paintings were from several epochs and artists and represent different subjects. More detailed information concerning these paintings is given elsewhere [35,42]. These 44 paintings were selected to minimize bias to a specific artist or painting style. To facilitate reading, the term "figurative" is used here to indicate the group of compositions with a realistic and accurate depiction of nature or of contemporary life; the term "abstract" is used to indicate the paintings that do not fall into the figurative group.

B. Data Analysis

The analysis of the chromatic properties of the natural scenes and paintings was carried out in the CIELAB color space. From the estimates of the spectral radiance from each pixel, and assuming the standard illuminant CIE D_{65}, the corresponding color was computed by converting radiance into tristimulus values for the CIE 1931 standard colorimetric observer and then converting into the CIELAB color space [43]. The properties analyzed were the gamut and the frequency of occurrence of the discernible colors.

1. Gamut

The color gamut of each painting and natural scene was obtained by projecting the colors in the CIELAB (a^*, b^*) plane. Only the colors that appeared more than 10 times in each image were considered in the analysis.

For each painting and natural scene, the limits of the gamut and its shape and orientation were characterized by the properties of an ellipse fitted to the data based on a least squares criterion. The ellipses calculated from the paintings and natural scenes cover on average 88% of the data points (standard deviation 2%). Axis ratios, angular position of the major axis, and areas were estimated. As an example, Fig. 2(b) shows the gamut and ellipses fitted for one natural scene (top row) and two paintings (middle and bottom rows).

2. Frequency of Occurrence of Discernible Colors

One way to characterize a distribution of colors is to identify the discernible colors present on the scene and to count how many times each occurs. Desaturated colors are, in general, more likely to appear than saturated ones, which are rare. A distribution like that has a maximum in the white region and decreases toward the periphery of the color space. Here,

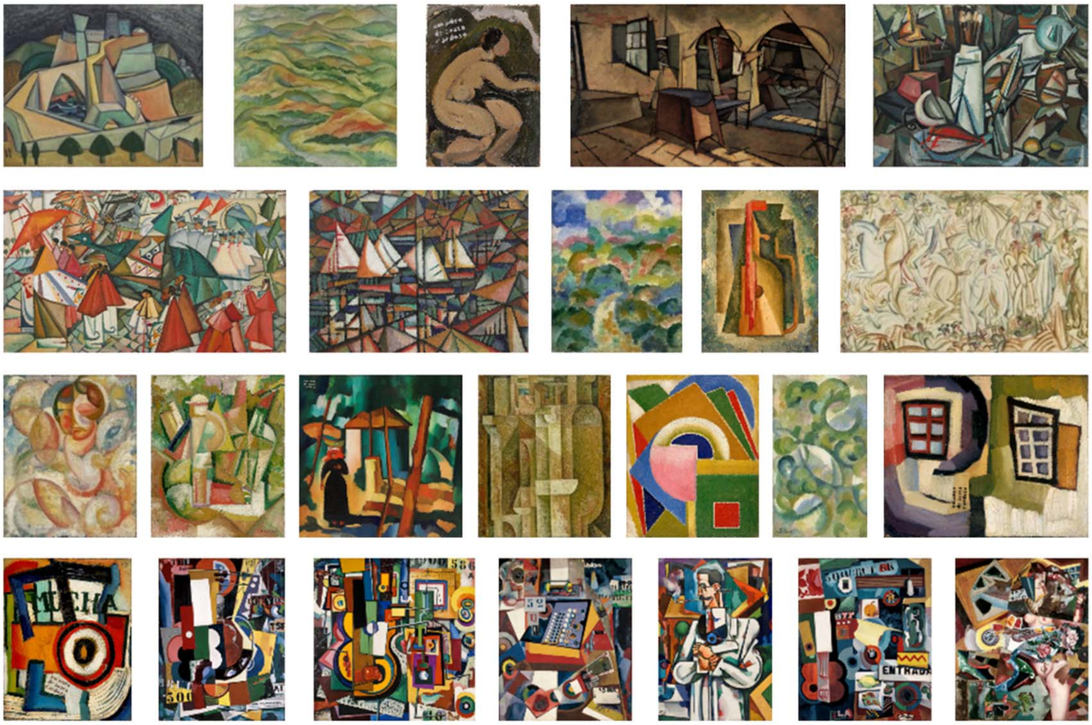

Fig. 1. Color thumbnails of the 24 paintings of Amadeo de Souza-Cardoso analyzed in this work (Photographic Archive CAM-FCG). The paintings are from the collection of the CAM-FCG in Lisbon. The other 20 paintings analyzed are from the collection of the Museu Nogueira da Silva, Braga, and are described in detail elsewhere [35,42]. For the analysis all paintings were digitalized with a hyperspectral system.

we characterized the color distribution in a different way, by computing the fraction of discernible colors expressed as a function of the number of times of occurrence in the scene or painting. Thus, we estimated the number of discernible colors and how many times each occurs, that is, the number of pixels that have that color. For the computation of the discernible colors the projection of the color volume in the CIELAB (a^*, b^*) plane was segmented into unitary squares and all colors inside each square were counted as one [13,47]. The number of times of occurrence is the number of individual pixels inside each square. Figure 3 illustrates the procedure. To better visualize the meaning of such analysis, imagine two extreme cases. In one case, there is only one color repeated in all pixels, like a uniform painting—all pixels will be represented in one square on Fig. 3. In another case, all colors of the gamut occur and with the same frequency—each square of Fig. 3 will have the same number of points. A real scene is expected to have a pattern somewhere in between these extreme situations. The question is what those patterns are and whether they are regular from scene to scene. Figure 2(c) shows an example for a natural scene (top row) and two paintings (middle and bottom rows). Interestingly, the fraction of discernible colors as a function of the occurrence is well described by a power law. Power laws are scale invariant and describe many natural properties [48], in particular, spatial properties of natural scenes [49]. Thus, these types of color distribution also show scale invariance in the color domain. To characterize each distribution a power function was fitted and the corresponding slope obtained.

3. RESULTS

A. Gamut Analysis

Figure 4 shows the color gamut for the 50 natural scenes (light gray dots) and for the 44 paintings (medium gray dots for Amadeo's paintings and dark gray for the paintings of the Museu Nogueira da Silva in Braga). The three gamuts are elongated in the yellow–blue direction. The gamut of the 44 paintings is smaller than that of natural scenes, but they have a comparable distribution. Moreover, the means of the two gamuts are very similar and close to the center of the CIELAB (a^*, b^*) plane: (1, 14) for the paintings and (−1, 11) for the natural scenes.

The analysis of the gamut of the individual paintings may also give stylistic information. The presence of data clusters in the CIELAB (a^*, b^*) plane is related with the presence of an almost monochromatic areas, without gradients of colors. In the case of the painting analyzed in Fig. 2 (bottom row), the cluster separate from the main group corresponds to the light yellow areas. This effect is quite evident in the geometric compositions; see, for example, the 15th painting in Fig. 1. The gamut of this painting in the CIELAB (a^*, b^*) plane is characterized by the presence of seven clusters of data corresponding to the main colors used in the composition.

Figure 5 shows the data obtained from the ellipses fitted to the colors of each scene and painting. The distributions of the areas, axis ratios, and angles are represented separately for the set of natural scenes and paintings. Figure 5(a) shows the two distributions for the areas expressed in CIELAB units. Symbols

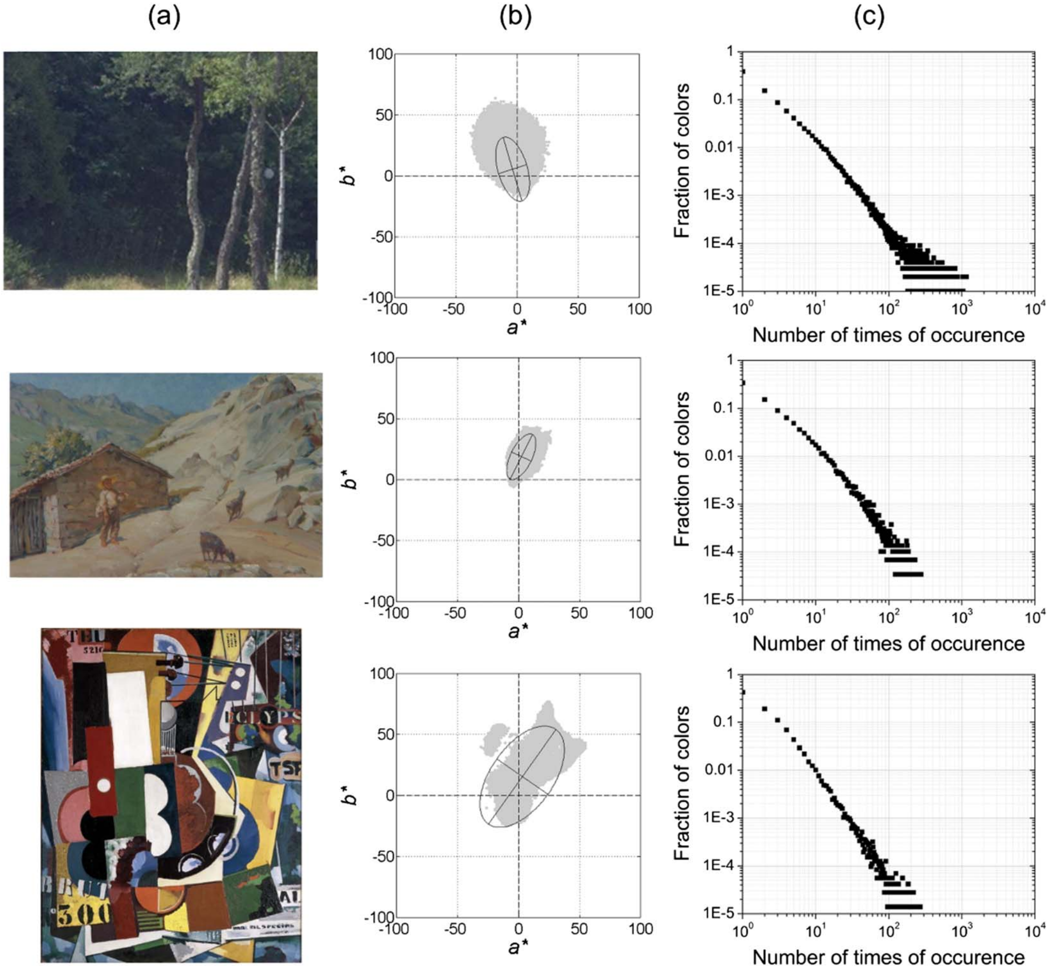

Fig. 2. Examples of gamut and frequency of occurrence of discernible colors for one natural scene and two paintings. The natural scene (top row) is from the Minho region of Portugal; the figurative painting (middle row) is from the collection of the Museu Nogueira da Silva in Braga, and the abstract painting (bottom row) is from Amadeo de Souza-Cardoso and belongs to the collection of the CAM-FCG in Lisbon. (a) Color images of the scenes and paintings. (b) Color gamut in the CIELAB (a^*, b^*) plane and corresponding best-fitting ellipses covering 88% of the data points. (c) Representation of the fraction of discernible colors expressed as a function of the number of times of occurrence in the scene or painting.

represent the data from the analysis and the lines represent the best-fitted exponentials to the data. The range of areas of the ellipses for the two classes of images is comparable. The range for natural scenes is 210–6,613 (average 1,226) and for the paintings 124–5,610 (average 1,338). Fractions of 92% for the natural scenes and 91% for the paintings are within the range 120–3,100. The distributions are therefore analogous. Similar ellipse areas mean similar gamut limits but not necessarily similar gamuts because the colors are not uniformly distributed within each ellipse. As shown in Fig. 4 the limits of the gamut of the natural scenes are larger than that of the paintings, despite the areas of the ellipses calculated for the two groups of images being comparable.

Figure 5(b) shows the distributions of the axis ratios. Symbols represent data from the analysis and the lines the best-fitted Gaussian distributions. There are also strong similarities between natural scenes and paintings in this case. The mean value calculated for the natural scenes is 0.51 and 0.58 for the paintings (0.56 for figurative paintings and 0.6 for abstract paintings). The distribution for the paintings is slightly shifted toward higher values when compared to the natural scenes. In other words, the distribution of colors in natural scenes is slightly more asymmetrical than in paintings. This effect is, however, small.

Figure 5(c) shows the distributions of angles of the ellipses. Symbols represent data from the analysis and the lines the best-fitted Gaussian distributions. The angle is defined by the major axis of the ellipse and the positive axis of the coordinate CIELAB a^*. The values from 0° to 90° indicate an ellipse whose major axis is rotated to the right of coordinate b^*, like in the paintings represented in Fig. 2(b) (middle and bottom rows). Values from 90° to 180° indicate an ellipse rotated toward the left of coordinate b^*, like the case of the natural scene presented in Fig. 2(b) (top row). The Gaussian curve fitting for the natural scenes is shifted toward higher values comparing with that of the paintings. Twenty-eight of the 50 images of natural scenes show an angle higher that 90°, while the same feature was observed in only 5 of the 44 paintings. The mean angle for the

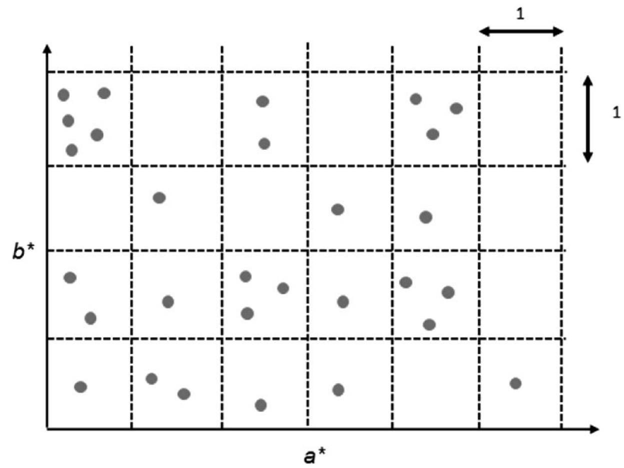

Fig. 3. Diagram to illustrate the procedure used to estimate the number of discernible colors and their frequency. Each gray circle represents one pixel. The projection of the color volume in the CIELAB (a^*, b^*) plane was segmented into unitary squares and all colors inside each square were counted as one [13,47]. The number of times of occurrence is the number of pixels inside each square. The fraction of discernible colors was expressed as a function of the number of times of occurrence in the scene or painting [see Fig. 2(c)].

natural scenes is 92° and 66° for the paintings (72° for the figurative and 58° for the abstract paintings). This is not a minor effect and the color gamut of the paintings is more tilted to red than in the natural scenes. This tilt effect in the ellipses does not mean that the greens are less used than the reds; rather, it means that the saturation balance favors reds over greens. Moreover it is important to note that representation of vegetation, trees, and natural landscapes does not necessarily imply a color gamut rotated in the same direction of the natural scenes (>90°). In the

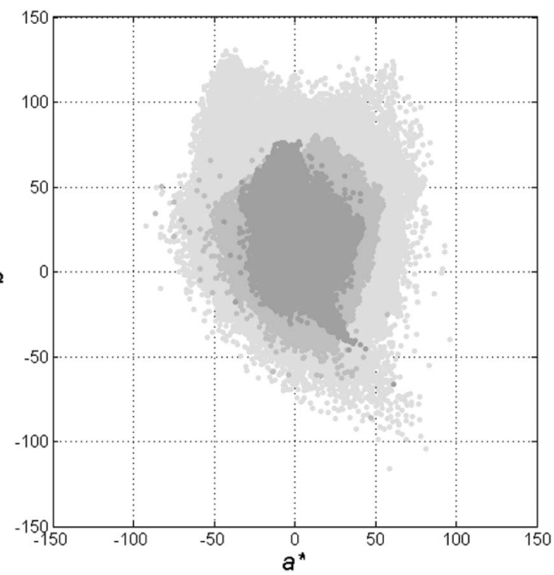

Fig. 4. Total color gamut in the CIELAB (a^*, b^*) plane for the 50 natural scenes (light gray dots), 24 paintings of Amadeo de Souza-Cardoso (medium gray dots), and 20 paintings from the collection of the Museu Nogueira da Silva in Braga (dark gray dots).

paintings database there is one painting depicting a verdant riverbank and the angle of the ellipse is 76°.

To confirm this angular effect we plotted the same information against two other databases of natural scenes. The dashed line represents the Gaussian fitting to the data obtained with a commercial hyperspectral camera at Harvard [50] and the pointed line represents best-fitted Gaussian to the data obtained with an in-house system at Bristol [1]. Both of these two distributions confirm the effect found here.

B. Frequency of Occurrence of Discernible Colors

Figure 6 shows the distribution of the slopes obtained by fitting power laws to the data represented in Fig. 2(c). Symbols represent data points and the lines best-fitted Gaussian distributions to the data points. The four images presented in the bottom part of Fig. 6 are examples of the extremes of the slope range. Lower slope values indicate the presence of few colors and almost monochromatic areas (images on the left); higher values of slope indicate more colors and less uniform areas (images on the right). Paintings and natural scenes have similar slope distribution, suggesting a common statistical distribution of colors. The mean slope calculated for the frequency of color occurrence in the natural scenes is −1.32 and −1.29 for the paintings (−1.28 in the figurative and −1.3 in the abstract paintings).

4. DISCUSSION AND CONCLUSIONS

Natural scenes and paintings have gamuts with shapes similarly elongated in the yellow–blue direction but more tilted to the red direction in paintings. It was also found that the fraction of discernible colors, expressed as a function of the times of occurrence in the scene or painting, is well described by a power law with similar distribution of slopes in a log–log scale. These features are observed in both figurative and abstract compositions. The elongation of the gamut in the yellow–blue direction is well known for natural scenes [11,12,44]. It is intriguing, however, that painters reproduce almost exactly the same statistical pattern.

Why do natural scenes and paintings share so many aspects except for the orientation of the gamut? It could be argued that our dataset of natural scenes is biased because of its size and nature. Yet, this effect is replicated with other independent databases of natural scenes and therefore it is unlikely to be explained by that aspect. It could also be argued that this is related to the nature of the representation or to the subject represented in the paintings set. It was observed that the mean angle for the figurative compositions is slightly higher than for abstract paintings (72° and 58°, respectively). Four out of the five paintings that show a considerable green component are figurative and just one is a nonfigurative painting. On the other hand, in the database there are 19 other figurative representations that do not have the same relevance in the green component. A strict correlation between the subject represented in the figurative paintings and the orientation of the gamut was not observed. The representation of vegetation, for example, does not necessarily imply a gamut oriented as in natural scenes.

The results presented here suggest that the underlying chromatic structure of the compositions generally follows the main

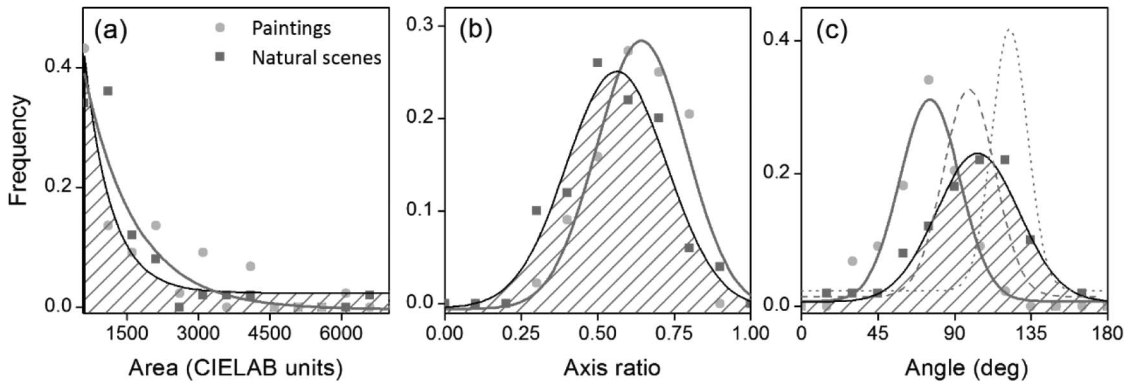

Fig. 5. Results from the analysis of the gamut of 50 natural scenes (dark gray squares) and of the 44 paintings (light gray circles). (a) Distribution of the areas of the ellipses fitted to the CIELAB (a^*, b^*) data. (b) Distribution of the ratios between the two axes of the ellipses. (c) Distribution of the angles of the longer axis of the ellipses with respect to the positive CIELAB a^* coordinate. The solid curves represent (a) best-fitted exponentials and (b) and (c) best-fitted Gaussians to the data. The dashed line represents the best-fitted Gaussian to the data obtained with a commercial hyperspectral camera at Harvard [50] and the pointed line represents Gaussian fitting to the data obtained with an in-house system at Bristol [1].

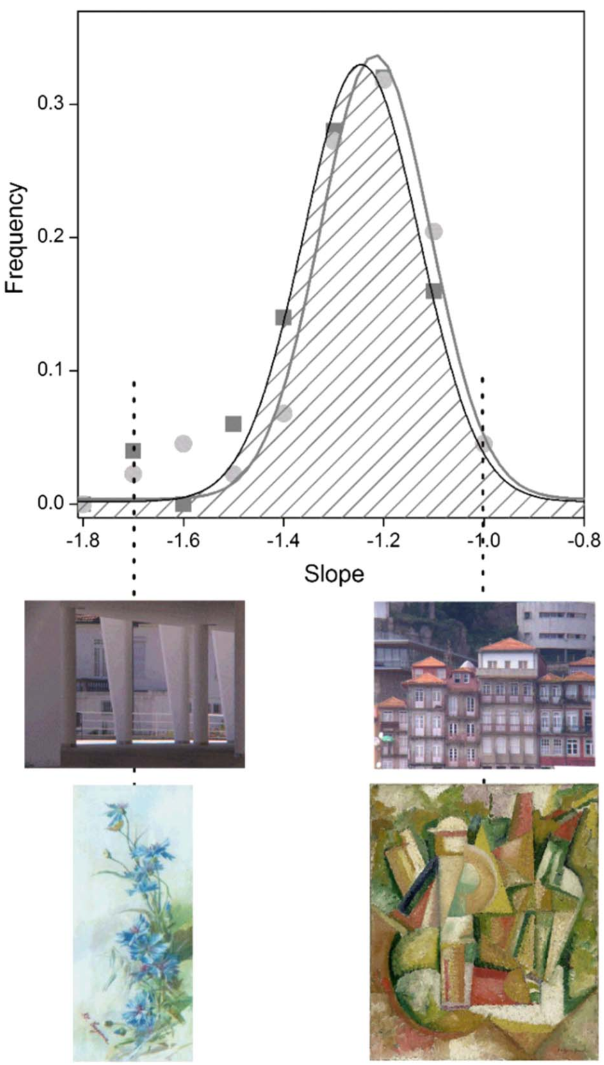

Fig. 6. Results from the frequency of occurrence analysis of the best-fit slopes of the power law for the 50 natural scenes (dark gray squares) and for the 44 paintings (light gray circles). The natural scenes and the paintings represented are examples of extremes of the slope range.

statistical features of the natural environment. Painters mimic the chromatic structure of natural scenes except for the balance between greens and reds. We conjecture two possibilities to explain the effect. They are related to the material and to the aesthetic of the painting. In the first case the limits imposed by the dyes and pigments available to the painters may influence the gamut of their compositions. Moreover, scientific analyses have detected many cases of chromatic alterations in green pigments. Is also known that there is a tendency of copper- and arsenic-based green pigments, such as Verdigris and Emerald green, to degrade and turn darker when used in oil media [51,52]. The second possibility is related to aesthetic choices made by the artist. For example, color preference is influenced by saturation and this influence depends on hue [23]; the imbalance between the red and green may be related to this phenomenon. Whether the gamut orientation is a voluntary option or not is still an open question.

Funding. Centro de Física of Minho University; Colour and Space in Cultural Heritage (COSCH); European Cooperation in Science and Technology (COST) (Action TD 1201); Fundação para a Ciência e a Tecnologia (FCT, Portuguese Foundation for Science and Technology) (PTDC/EAT-EAT/113612/2009, PTDC/MHC-PCN/4731/2012, SFRH/BD/66488/2009); FEDER through the COMPETE Program.

Acknowledgment. This work has been supported by national funds through FCT–Fundação para a Ciência e a Tecnologia (Portuguese Foundation for Science and Technology) under project PTDC/EAT-EAT/113612/2009 and grant SFRH/BD/66488/2009. Support was also provided by the Centro de Física of Minho University, by FEDER through the COMPETE Program, by the Portuguese Foundation for Science and Technology (FCT) in the framework of the project PTDC/MHC-PCN/4731/2012, and by the European Cooperation in Science and Technology and the COST-Action TD 1201: Colour and Space in Cultural Heritage (COSCH). The authors are grateful to all team members of CAM–Centro de Arte Moderna da Fundação Gulbenkian in Lisbon (Portugal) for the fruitful collaboration, in particular to director Isabel Carlos, curator Ana Vasconcelos e Melo, and photographer Paulo Costa. The authors also acknowledge Osamu Masuda and Hélder Tiago Correia for helping in the spectral imaging of the paintings.

REFERENCES

1. C. A. Parraga, G. Brelstaff, T. Troscianko, and I. R. Moorehead, "Color and luminance information in natural scenes," J. Opt. Soc. Am. A **15**, 563–569 (1998).
2. C. A. Parraga, T. Troscianko, and D. J. Tolhurst, "The human visual system is optimised for processing the spatial information in natural visual images," Curr. Biol. **10**, 35–38 (2000).
3. C. A. Parraga, T. Troscianko, and D. J. Tolhurst, "Spatiochromatic properties of natural images and human vision," Curr. Biol. **12**, 483–487 (2002).
4. D. J. Tolhurst, Y. Tadmor, and T. Chao, "Amplitude spectra of natural images," Ophthalmic Physiolog. Opt. **12**, 229–232 (1992).
5. G. A. Cecchi, A. R. Rao, Y. P. Xiao, and E. Kaplan, "Statistics of natural scenes and cortical color processing," J. Vis. **10**(11):21, 1–13 (2010).
6. C. C. Chiao, T. W. Cronin, and D. Osorio, "Color signals in natural scenes: characteristics of reflectance spectra and effects of natural illuminants," J. Opt. Soc. Am. A **17**, 218–224 (2000).
7. S. M. C. Nascimento, D. H. Foster, and K. Amano, "Psychophysical estimates of the number of spectral-reflectance basis functions needed to reproduce natural scenes," J. Opt. Soc. Am. A **22**, 1017–1022 (2005).
8. T. W. Lee, T. Wachtler, and T. J. Sejnowski, "Color opponency is an efficient representation of spectral properties in natural scenes," Vis. Res. **42**, 2095–2103 (2002).
9. W. Geisler, "Visual perception and the statistical properties of natural scenes," Ann. Rev. Psych. **59**, 167–192 (2008).
10. A. D. D'Antona, J. S. Perry, and W. S. Geisler, "Humans make efficient use of natural image statistics when performing spatial interpolation," J. Vis. **13**(14):11, 1–13 (2013).
11. M. A. Webster and J. D. Mollon, "Adaptation and the color statistics of natural images," Vis. Res. **37**, 3283–3298 (1997).
12. K. C. McDermott and M. A. Webster, "Uniform color spaces and natural image statistics," J. Opt. Soc. Am. A **29**, A182–A187 (2012).
13. J. M. M. Linhares, P. D. Pinto, and S. M. C. Nascimento, "The number of discernible colors in natural scenes," J. Opt. Soc. Am. A **25**, 2918–2924 (2008).
14. D. H. Foster, K. Amano, S. M. C. Nascimento, and M. J. Foster, "Frequency of metamerism in natural scenes," J. Opt. Soc. Am. A **23**, 2359–2372 (2006).
15. T. Hansen and K. T. Gegenfurtner, "Independence of color and luminance edges in natural scenes," Vis. Neurosci. **26**, 35–49 (2009).
16. S. M. Nascimento, K. Amano, and D. H. Foster, "Spatial distributions of local illumination color in natural scenes," Vis. Res., doi:10.1016/j.visres.2015.07.005 (to be published).
17. P. Cavanagh, "The artist as neuroscientist," Nature **434**, 301–307 (2005).
18. S. Zeki, *Inner Vision: An Exploration of Art and the Brain* (Oxford University, 1999).
19. B. R. Conway, "Color consilience: color through the lens of art practice, history, philosophy, and neuroscience," Ann. N. Y. Acad. Sci. **1251**, 77–94 (2012).
20. P. Mamassian, "Ambiguities and conventions in the perception of visual art," Vis. Res. **48**, 2143–2153 (2008).
21. D. J. Graham and M. Meng, "Artistic representations: clues to efficient coding in human vision," Vis. Neurosci. **28**, 371–379 (2011).
22. A. Chatterjee, "Neuroaesthetics: a coming of age story," Cogn. Neurosci. **23**, 53–62 (2010).
23. S. E. Palmer, K. B. Schloss, and J. Sammartino, "Visual aesthetics and human preference," Ann. Rev. Psych. **64**, 77–107 (2013).
24. D. J. Graham and D. J. Field, "Statistical regularities of art images and natural scenes: spectra, sparseness and nonlinearities," Spatial Vis. **21**, 149–164 (2008).
25. D. J. Graham and C. Redies, "Statistical regularities in art: relations with visual coding and perception," Vis. Res. **50**, 1503–1509 (2010).
26. R. P. Taylor, A. P. Micolich, and D. Jonas, "Fractal analysis of Pollock's drip paintings," Nature **399**, 422 (1999).
27. D. Fernandez and A. J. Wilkins, "Uncomfortable images in art and nature," Percept. **37**, 1098–1113 (2008).
28. C. Redies, J. Hasenstein, and J. Denzler, "Fractal-like image statistics in visual art: similarity to natural scenes," Spatial Vis. **21**, 137–148 (2007).
29. L. R. M. Barros, *A cor no processo creativo. Um estudo sobre a Bauhaus e a teoria de Goethe*, 2nd ed. (Senac São Paolo, 2007).
30. G. Mather, "Colour in art," in *The Psychology of Visual Art: Eye, Brain and Art* (Cambridge University, 2014), pp. 109–121.
31. J. I. Berezhnoy, E. Postma, and J. van den Herik, "Computer analysis of van Gogh's complementary colours," Patt. Recog. Lett. **28**, 703–709 (2007).
32. J. I. Berezhnoy, "Digital analysis of paintings," Ph.D. dissertation (Tilburg University, 2009).
33. J. Rigau, M. Feixas, M. Sbert, and C. Wallraven, "Toward Auvers period: evolution of van Gogh's style," in *Computational Aesthetics 2010: Proceedings of the Sixth International Conference on Computational Aesthetics in Graphics, Visualization, and Imaging* (Eurographics Association, 2010), pp. 99–106.
34. Y. Zhao, R. S. Berns, L. A. Taplin, and J. Coddington, "An investigation of multispectral imaging for the mapping of pigments in paintings," Proc. SPIE **6810**, 681007 (2008).
35. P. D. Pinto, P. E. R. Felgueiras, J. M. M. Linhares, and S. M. C. Nascimento, "Chromatic effects of metamers of D65 on art paintings," Ophthalmic Physiol. Opt. **30**, 632–637 (2010).
36. C. Li and T. Chen, "Aesthetic visual quality assessment of paintings," IEEE J. Select Topics Signal Process. **3**, 236–252 (2009).
37. B. Mallon, C. Redies, and G. U. Hayn-Leichsenring, "Beauty in abstract paintings: perceptual contrast and statistical properties," Front. Hum. Neurosci. **8**, 1–14 (2014).
38. E. A. Vessel, G. G. Starr, and N. Rubin, "Art reaches within: aesthetic experience, the self and the default mode network," Front. Neurosci. **7**, 1–9 (2013).
39. V. Yanulevskaya, J. Uijlings, E. Bruni, A. Sartori, E. Zamboni, and F. Bacci, "In the eye of the beholder: employing statistical analysis and eye tracking for analyzing abstract paintings," in *MM '12: Proceedings of the 20th ACM International Conference on Multimedia* (ACM, 2012), pp. 349–358.
40. F. Cutzu, R. Hammoud, and A. Leykin, "Distinguishing paintings from photographs," Comp. Vision Image Understanding **100**, 249–273 (2005).
41. A. Leykin and F. Cutzu, "Differences of edge properties in photographs and paintings," in *International Conference on Image Processing (ICIP)* (IEEE, 2003), pp. 541–544.
42. P. D. Pinto, J. M. M. Linhares, and S. M. C. Nascimento, "Correlated color temperature preferred by observers for illumination of artistic paintings," J. Opt. Soc. Am. A **25**, 623–630 (2008).
43. CIE, "Colorimetry," in *CIE* (2005), pp. 1–82.
44. S. M. C. Nascimento, F. P. Ferreira, and D. H. Foster, "Statistics of spatial cone-excitation ratios in natural scenes," J. Opt. Soc. Am. A **19**, 1484–1490 (2002).
45. M. J. Melo, M. Vilarigues, S. Babo, C. Alfaro, H. Freitas, and I. Sandu, "Uma mão cheia de cores, o século XX e o nascimento da arte Moderna," in *Amadeo de Souza-Cardoso, Catalogue Raisonné, Pintura* (Assírio & Alvim and Fundação Calouste Gulbenkian, 2008), pp. 81–104.
46. C. Montagner, "The brushstroke and materials of Amadeo de Souza-Cardoso combined in an authentication tool," Ph.D. dissertation (Faculdade de Ciências e Tecnologia–Universidade NOVA de Lisboa, 2015).

47. M. R. Pointer and G. G. Attridge, "The number of discernible colours," Color Res. Appl. **23**, 52–54 (1998).
48. C. M. A. Pinto, A. M. Lopes, and J. A. T. Machado, "A review of power laws in real life phenomena," Commun. Nonlinear Sci. Numer. Simul. **17**, 3558–3578 (2012).
49. D. L. Ruderman, "Origins of scaling in natural images," Vis. Res. **37**, 3385–3398 (1997).
50. A. Chakrabarti and T. Zickler, "Statistics of real-world hyperspectral images," in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition* (IEEE, 2011), pp. 193–200.
51. K. Keune, J. J. Boon, R. Boitelle, and Y. Shimadzu, "Degradation of emerald green in oil paint and its contribution to the rapid change in colour of the Descente des vaches (1834–1835) painted by Théodore Rousseau," Stud. Conserv. **58**, 199–210 (2013).
52. M. H. van Eikema Hommes, *Changing Pictures: Discoloration in 15th–17th Century Oil Paintings* (Archetype, 2004).