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Aesthetics and Entropy. IV. Image Composition and Content

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Abstract

In this preliminary work we created a database of ten images representative of typical digital photographic imagery, and evaluated both the Birkhoff [4,18] and Eysenck [23] aesthetic measures, *M*, for each. We then used the methodology of Liu *et al*. [26] to assess a compositional figure of merit, *EA*, for each of the test images. We found a significant correlation between *EA* and entropy, which implies a commonality between informational and compositional features of an image.

The images were then presented to a panel of experienced observers from the arts community, and a rank order for aesthetic merit was determined from their evaluations. Although the rank order correlated weakly with the Eysenck aesthetic measure, a much stronger correlation was observed with the compositional metric characterizing adherence of the composition of the image to the rule of thirds, suggesting that adherence of the composition to the rule of thirds dominates sophisticated observers' intuitive apprehension of the aesthetic value of the image. These results render problematical the attempt to establish an exclusively information theory-based aesthetic measure.

Introduction

This study is a continuation of our previous work; in the initial phase our objective was to demonstrate the information theoretical basis for the preference in fine art photography of either "high key" of "low key" images [1]. We then extended our work to consider various approaches using information theory to develop a quantitative "aesthetic measure", i.e., an aesthetic figure-of-merit, *M*, and applying these approaches to digital photography [2,3]. We envision such a metric to be of potential value not only for the psychological insight it may provide into the appreciation of beauty by the human mind, but as a response to guide image optimization by a fully automated, e.g., evolutionary operation, image processing algorithm.

A limitation of the information theoretical approach is that, following Birkhoff [4], it considers only the informational aspects of an image, and not directly the compositional aspects of the image, known to play an important role in image aesthetics. Pleasing composition is an important concern of practicing photographers [5]. It has been said that, "Composition is everything when it comes to photography" [6]. Despite his theoretical approach, Birkhoff recognized that image composition was essential to order and comprehensibility in an image, "…it is decidedly interesting to remark in this connection how a fine composition is always arranged so as to be easily comprehensible." (Birkhoff, as quoted by blogger Megan Power [7]). The current extension of our work is directed to selecting an objective metric for evaluating photographic composition and incorporating it, along with the information-theory based measures, to find an overall figure-of-merit for a photographic work of art. This approach will also enable an evaluation of the connection between compositional merit and image order, as estimated by compressibility, *K*. We envision that an overall aesthetic figure-of-merit for photographic images may have a variety of real-world applications, including photographic education, curating of photo collections, and image selection for advertising and decorative purposes, as well as becoming an element in automated image processing schemes and assisting in implementation of photo enhancement algorithms.

Most recent work on development of a theory-based metric for aesthetic classification of images has emphasized deep learning based on large data sets, to exploit the power of Artificial Intelligence. In so doing, the problem of aesthetic classification becomes a data-driven machine learning problem. The goals of this work have included aesthetic-aware color enhancement and image cropping and re-composition, among others. This field of endeavor has recently been reviewed by Zhang and co-workers [8]. The approaches taken, while encouraging, are unattractive to us, both in terms of the large data sets and computational requirements, as well as the lack of transparency the approach offers to understanding the most fundamental aspects of images which make them attractive to viewers, i.e., as already pointed out by Aydin and co-workers it does not explain why an image is pleasing or not [9]. For this latter reason we continue to pursue the goal of aesthetic evaluation based on low-level features. These authors, however, consider composition to be a "sub-problem".

The topic of the quantitative description of beauty continues to be of interest in the scientific community [10,11]. Some of the questions being addressed include the role of subjectivity in aesthetic perception [12] and whether more or less complex images are preferable [13,14], a discussion which has continued since it was first addressed by Berlyne [15].

Aesthetic Measures

Elucidation of a figure-of-merit for the aesthetic quality of an art work has been the subject of research interest since BIrkhoff published his seminal book on the subject in 1933 [4]. Birkhoff proposed that beauty can be perceived through the interplay of complexity and order. His work has been reviewed critically in the light of recent research by Douchova [16]. An implicit assumption in the search for an aesthetic measure is the universality of aesthetic experience, as hypothesized by Berlyne [15] and Huntley [17].

The Birkhoff aesthetic measure, *M*, has been given mathematical expression in a variety of forms. Bense [18] has written

$$M = (S - K^{-1})/S. \tag{1}$$

In place of S we use $(1 + \Delta S)$ where ΔS is the difference between image entropy, *S,* and the entropy, S_o, of a similar-sized image comprising white noise, i.e., $\Delta S = (S - S_o)$ and $0 \leq (1 + \Delta S) \leq 1$; *K* is in our usage the reciprocal of image compressibility, taken as a surrogate for the order represented by the internal logic of the image. In the context of information theory, entropy reflects information content of an image, such that the most negative value of ΔS corresponds to the image with lowest information content. Accordingly Eq. (1) reduces to [7]

$$M = 1/K(1 + \Delta S). \qquad (2)$$

Studies on the relationship between brightness distribution and entropy have associated higher contrast with higher entropy [19]. More recently, however, Khalili and Bouchachia [11] found no correlation between energy of an image, defined as the gradient of the brightness distribution, i.e., contrast, and entropy for a large population of abstract test images. But Singnoo and Finlayson found that contrast optimization for observer preference corresponded to a maximum entropy condition for the real photographic images they studied [20]. Agaian and co-workers have used entropy as a response metric for image enhancement, e.g., by contrast enhancement and histogram equalization [21].

Rigau *et al*. have concluded in their development of "computational aesthetics" that the aesthetic figure-of-merit can be based on Shannon entropy alone [22]. According to Eysenck [23] aesthetic response can be expressed as the product of order and complexity; thus

$$M = (1 + \Delta S) /K. \qquad (3)$$

The validity of Eysenck's approach, which implies the desirability of complexity, has not been universally shared, according to Burns, who has critically reviewed the various approaches to a purely nformation-based aesthetic figure-of-merit [10].

Evaluation of Composition

For the past decade attempts to quantify the contribution of composition to the aesthetic quality of an image have been directed primarily to the exploitation of artificial intelligence (AI) [24-26]. Major task has been the accumulation of a database of images which have been subjectively evaluated by a number of observers for use as a learning set to enable a neural network to reliably score new images. Such an approach, while useful and interesting, requires a large-scale computing capability, as well as database access. A simpler and more straightforward method, a so-called "lower-level" approach, based on first principles of composition may also be feasible to provide a single compositional figure-of-merit. Liu, Chen, Wolf, and Cohen-Or have published a technical report outlining just such a method, in their case as a means to implementing an automated image cropping method [26]. Their compositional metric is designated *EA*.

A more complicated approach which evaluated up to 55 compositional factors was proposed by Obrador and co-workers [27]. They found that low-level image composition features could be used to parameterize a model that yielded close to state-of-the art aesthetic-based classification accuracy (*vis-à-vis* AI-based high -level approaches). In that analysis features reflecting visual balance proved the most significant, statistically, and only 6-10 compositional factors were actually significant in parameterizing their model. Identification of these factors was a major objective of their study. One reason for the complexity of their approach was the use of an image database comprising color photographs, which introduced the role of color in aesthetic response. In order to avoid the complexities introduced by color and focus on basic compositional elements, in the present study we use only monochrome images and adopt the modeling approach of Liu *et al.* [26].

The principal compositional elements addressed in the model of Liu [26], each of which are evaluated separately are:

- rule of thirds, *E(RT)*;
- diagonal lines, *E(DA)*; and
- optical balance, *E(BA)*.

Then,

$$EA = [E(RT) + 0.3E(D) + E(BA)]/2.3. \qquad (4)$$

To evaluate an image's compliance with rule of thirds, the frame is divided vertically and horizontally into thirds with lines; the intersections of these lines are the so-called "Power Points". These Power Points are approximations to the location of the center of interest of a two-dimensional image along a diagonal of that image at a point corresponding to the Euclidian "Golden Ratio", as advocated by Leonardo DaVinci in 1509 (*De divina proportione*) [17,28]. Lauren Scott [28] has presented arguments for the advantages of the "rule of thirds" approximation over rigorous application of the Golden Ratio. In Liu *et al*.'s algorithm, the Euclidian distance, D_1, of the image's center of interest from the nearest Power Point is used to estimate *E(RT,point)*, where D_1 is measured in units of pixels normalized by the number of pixels along a parallel line extending the full length or width of the image frame. D_1 is thus dimensionless and can have a value between 0 and unity.

$$E(RT,point) = exp(-D_1^2/\sigma). \qquad (5)$$

Likewise, *D* for a horizontal or vertical line, parallel to one of the dividing lines, is the normalized Euclidian distance between that line and the dividing line. *E*(*RT,line*) is then obtained analogously to *E*(RT,point) using Eq. (5). Accordingly,

$$E(RT) = a\ E(RT,point) + (1 - a)\ E(RT,line) \qquad (6)$$

where a is a constant. According to Liu et al., a = 1/3 and σ = 0.34. In our work we chose to let σ = 0.05, in order to make fullest use of the scale $0 \leq E(RT) \leq 1$. For images which did not have a strong horizontal or vertical line we let *E(RT)* = *E(RT,point)*.

E(DA) is defined similarly; in this case D_2 is the normalized distance between a prominent diagonal line in the image and a diagonal axis of the frame, averaged along the length of the line. Eq. (7) is analogous to Eq. (5),

$$E(DA) = exp(-D_2^2/\sigma) \qquad (7)$$

where σ is undefined in Ref. [26] and σ = 0.02 in our work.

The method of Liu *et al*. [26] for evaluating *E(BA)* did not prove straightforward to implement on our hands and yielded some counterintuitive results. We therefore modified it as follows. A vector was drawn from the center of the image frame to each optical mass in the image; a center of optical mass was then found by vector addition. D_3 was estimated as the normalized Euclidean distance between this center of mass and the center of the frame, and

$$E(BA) = exp(-D_3^2/\sigma) \quad (8)$$

with σ = 0.0125. Centers of optical mass, i.e., centers of interest, in the images were identified by visual inspection. Liu *et al*. also include a response to represent right-sizing of the principal subject matter of the image *E(SZ),* which is relevant to their cropping application. As the test images to be used in the present study were all professional quality, properly framed or, in some cases, cropped, it was unnecessary to include this response in Eq. (4), as it would not provide any additional measure of distinction among the images.

Methodology

Although a variety of public databases exist for photo-aesthetics evaluation, these in general are too large for the purposes of the present study, and the images do not necessarily lend themselves to information theoretical evaluation in straightforward fashion, insofar as they have been acquired under various unspecified conditions and uncontrolled conditions of exposure, lighting, etc., using a wide variety of devices. Most digital photography databases furthermore comprise color images, and we wished to avoid the complexities introduced by color [19]. Therefore we selected ten photographs more-or-less arbitrarily from the author's collection of about 47,000 images as test images. Each represents a different genre of photography:

- *Capybaras*—animals in nature;
- *Flag*—semi-abstract graphic;
- *Garden Goddess*—image of an art work;
- *Kavanaugh*—architecture;
- *Merced River*—figure study;
- *Moon Shot*—astronomical object in night sky;
- *Oak Park*—landscape;
- *Pasque Flower*—nature close-up.

Four of these photos are low-key; two are high-key, and the remining four fall into neither category. All but two of the photographs were taken on an 8MP Canon EOS Rebel™ digital SLR camera; the remaining two (*Veronica* and *Pasque Flower*) were captured with the camera of an iPhone7 (2.5MP). Copyright to all original images is retained by the photographers.

Figure 1. Left to right top row: *Capybaras, Flag, Garden Goddess, Kavanaugh*, and *Merced River;* bottom row: *Moon Shot*, *Oak Park, Pasque Flower, Rocks*, and *Veronica*.

The images were imported into Adobe Photoshop Elements™ version 11, where the originally RGB photos were converted to monochrome. Thumbnails of the images are shown in Figure 1. The two images which had been cropped by the photographer (*Moon Shot* and *Merced River*) and the two iPhone images were resized to 8MP using the bicubic interpolation algorithm in the Photoshop app, so that entropy estimates would be comparable for all images. Unsharp masking was implemented with a radius of 1.6 pixels and a level of 50%, comparable to the practice of professional photographers [30]. One rationale for enhancing photographs with unsharp masking is that it is one of the image processing steps which occur in the human retina prior to encoding visual information for transmission by the optic nerve [31-33]. Brightness histograms of the images were obtained before and after addition of unsharp masking at this level and found to be indistinguishable.

Files were saved in both bitmap (.BMP) and GIF formats to enable estimation of image compressibility, as $1/K$, where K is the ratio of GIF to BMP file sizes. The GIF format was chosen because psychophysical studies have shown GIF compressibility to correlate better with perceived image attractiveness, i.e., "beauty" [14]. In that psychophysical study it was also inferred that GIF compressibility provides the best automated estimate of algorithmic, i.e., Kolmorgorov, complexity, of the image.

Distances for evaluation of Eqs. (5) – (8) and amplitudes of the brightness histograms (for entropy calculation—see below) were measured using the on-screen cursor coordinates and manually entered into a Microsoft Excel™ (version 16.48) spreadsheet. All calculations were carried out in Excel.

Image entropy, S, was calculated from the brightness histograms of the images as saved in bitmap

$$S = -k\sum p(x)\ ln\ p(x), \qquad (9)$$

where $p(x)$ is the fractional number of pixels in the xth brightness channel ($1 \leq x \leq 256$) and k is the Boltzmann constant. Note that Eq. (9) provides the Gibbs entropy of each brightness channel, so that S corresponds to the Shannon entropy of the image. In our previous work [1-3] we had used Boltzmann entropy, so entropies calculated in this work are not numerically eqivalent to those reported for the same images (*Flag*, *Rocks* and *Oak Park*) where used in the previous work. We then define $\Delta S = (S - S_o)$, where S_o is the entropy of a frame of white noise, $S_o = 5.545k$; as noted above ΔS as $(1 + \Delta S)$ is used for evaluation of Eqs. (2) and (3). Statistical significance of correlations was established using the t-test; for a data set of the size employed here a threshold of $t = 2$ (95% confidence level) requires $r \geq 0.57$, and a threshold of $t = 1.4$ (90% confidence level) requires $r \geq 0.40$.

Five observers experienced in dealing with photographic art were asked to evaluate the images by their own individual criteria. These individuals were:

A – pictorial photographer, art collector and sometime salon adjudicator;
B – photographer, art installer and interior designer;
J – commercial gallery curator;
M – architect and costume designer;
N – free-lance artist, arts administrator and sometime curator of an important public art collection.

Three of the above are male; two are female.

They were individually shown the images in a "slide-sorter" window of a laptop computer and asked to organize them in the slide-sorter according to their preferences. Subjective commentary on the individual images was discouraged. The most preferred image was scored "1" and the least preferred "10". The scores were averaged to produce a consensus score, which were then converted to a rank order, *R*, for the images. As evidenced by the correlation coefficients, *r*, for the regression analyses of the individual scores with the consensus, four of the observers were in reasonable agreement with each other, while one observer, B, represented a different point of view. Observer B's ratings were included in the consensus figures, however.

Results and Discussion

The information-theoretical responses for the test images are given in Table 1. Entropy, as $(1 + \Delta S)$, and compressibility, $1/K$, are, as expected, significantly inversely correlated, $r = -0.576$. This relationship between entropy and lossless compression has already been noted by Bassiou and Kotropoulos [18] and supports to a certain extent the interpretation of Rigau [21] that image entropy reflects disorder, which is understood to be measured by K. Intuitively one might expect a more complex image to be less compressible. Aesthetic measures, M, calculated according to Eqs. (2) and (3), are given in Table 1. From the entropy data it can be inferred that *Moon Shot* has the lowest information content, while *Garden Goddess* and *Pasque Flower* have the highest. With respect to the aesthetic measures, the Birkhoff measure predicts *Moon Shot* to be the most desirable image, while the Eysenck formulation predicts *Pasque Flower*.

Table 1

Image	$(1+\Delta S)$	$1/K$	M[Eq.(2)]	M[Eq.(3)]
Capybaras	0.786	3.135	3.989	2.464
Flag	0.457	4.651	10.177	2.126
Garden Goddess	0.865	3.436	3.972	2.972
Kavanaugh	0.621	4.016	6.467	2.494
Merced River	0.565	4.566	8.081	2.580
Moon Shot	0.114	4.132	36.344	0.472
Oak Park	0.636	3.322	5.223	2.113
Pasque Flower	0.862	4.000	4.640	3.448
Rocks	0.759	3.390	4.466	2.573
Veronica	0.808	3.371	4.171	2.72

Table 2

Image	*E(RT)*	*E(DA)*	*E(BA)*	*EA*
Capybaras	0.399	0.813	0.198	0.366
Flag	0.561	0.494	0.750	0.584
Garden Goddess	0.458	0.775	0.981	0.669
Kavanaugh	0.800	0.520	0.593	0.620
Merced River	0.899	0.606	0.000	0.432
Moon Shot	0.801	0.004	0.000	0.321
Oak Park	0.878	0.004	0.593	0.589
Pasque Flower	0.760	0.741	0.675	0.663
Rocks	0.000	0.775	1.000	0.493
Veronica	0.954	0.832	0.957	0.864

Table 3.

Image	A	B	J	M	N	Avg.	R
Capybaras	4	9	7	10	2	5.8	5
Garden Goddess	5	10	3	6	7	6.2	6.5
Kavanaugh	9	3	6	9	10	7.4	9
Merced River	2	8	4	1	1	3.2	2
Moon Shot	6	5	9	3	8	6.2	6.5
Oak Park	3	1	2	2	3	2.2	1
Pasque Flower	7	4	1	4	5	4.2	3
Rocks	10	6	5	8	9	7.6	10
Veronica	1	7	8	7	4	5.4	4
r	0.61	0.28	0.57	0.72	0.78		

Compositional merit was evaluated for each of the images according to Eq. (4). The figures-of-merit, *EA*, are given in Table 2, along with values for the component factors representing contributions from rule of thirds, *E(RT)*, diagonal elements, *E(DA),* and optical balance, *E(BA)*. The *EA* values do not correlate significantly with *M* values calculated either according to Eq. (2) or Eq. (3), but show a significantly positive correlation (r = 0.565) with image entropy, $(1 + \Delta S)$. Thus entropy reflects to some extent compositional as well as informational factors. Perhaps more complex images lend themselves to more sophisticated composition. This inference needs to be explored further. On the basis of compositional merit alone, it appears that *Veronica* should be the most preferred image.

The rankings of the images provided by the panel of observers are given in Table 3, along with a consensus ranking. From the latter an aesthetic rank order, *R*, for the individual images was determined. The mid-range ranking of the portrait *Veronica* is somewhat surprising given the importance of human faces to image appeal [34]. Regression of the rank order for each of the images, *R*, on each of the calculated aesthetic figures-of-merit yielded correlation coefficients shown in Table 4. Since a lower *R*-value corresponds to an image found more desirable on the part of the observers, a negative correlation coefficient is to be expected for a metric which successfully predicts aesthetic merit.

Table 4.

Correlation coefficients for regression of *R* on:

K	-0.242
$(1+\Delta S)$	-0.016
$E(RT)$	-0.700
$E(DA)$	0.437
$E(BA)$	0.180
EA	-0.264
M [Eq. (2)]	0.068
M [Eq. (3)]	-0.113

Correlations of observer preference with the information theoretical responses and the figures-of-merit from Table 2 are extremely weak. These correlations were not improved by linear combination of the aesthetic measures with *EA.* Note that image entropy, $(1 + \Delta S)$, is essentially uncorrelated with observer preference, despite its previously observed utility for optimizing exposure and contrast [1,19,20]; this result is, however, consistent with that of Ref. [11].

Observer preference was relatively weakly correlated with the compositional figure-of-merit, *EA*, itself. Further examination of the data, however, showed that a highly significant correlation ($r = -0.700$) existed, however, between the rank ordering of the images and the rule of thirds metric, $E(RT)$, from Eq. (6) and Table 2. Such correspondence is consistent with Huntley's understanding of aesthetics [17] and the central role of the so-called Golden Ratio. In this regard our results appear to contradict those of Amirshahi and co-workers who concluded on the basis of evaluating a large body of high-quality photographs and paintings that the rule of thirds plays only a minor role in the aesthetic valuation of works of art [35].

The correlation coefficient for rank order, *R*, with the figure-of-merit for diagonal elements, $E(DA)$ was also significant, but positive. Most likely this result is artifactual, given the limited database of images. Optical balance of the image, as evaluated here, correlated only weakly and negatively with observer preference, although this had been the most significant compositional factor in the analysis of Obrador et al. [27]. Conformance to the rule of thirds thus dominated the intuitive apprehension of good composition on the part of the seasoned observers. Thus $E(RT)$ appears to be the most promising metric for predicting observer apprehension of the aesthetic quality of an image, and leads to the conclusion that composition is the dominant determinant of aesthetic experience. This conclusion predicates improvement of the modeling strategy of Liu *et al*., by re-weighting the elements contributing to the summary compositional metric, *EA*, and by addition of other compositional elements of known importance in photographic practice, e.g., framing and S-curves [5]. We emphasize the importance of understanding the role of compositional factors in the appreciation of monochrome imagery before attempting to deal with the complexities of color.

Summary and Conclusions

In this work we created a database of ten images representative of typical digital photographic imagery, and evaluated both the Birkhoff [4,7] and Eysenck [23] aesthetic measures, *M*, for each. A shortcoming of the proposed aesthetic measures is that they do not take into consideration image composition, i.e., the spatial arrangement of image elements, despite its established aesthetic importance [5]. We accordingly used the methodology of Liu *et al*. [26] to assess a compositional figure of merit, *EA*, for each of the test images. We found a significant correlation between *EA* and *S*, which implies a commonality between informational and compositional features of an image. On the other hand, there was no statistically significant correlation between compositional merit and compressibility.

The images were presented to a panel of experienced observers and a rank order for aesthetic merit was determined from their evaluations. The observers' preferences did not correlate with the information-theory based aesthetic measures. The only strong correlation observed was between rank order and the compositional metric characterizing adherence of composition to the rule of thirds. This relationship suggests that adherence of the composition to the rule of thirds dominated the observers' intuitive apprehension of the aesthetic value of the image. In summary the results support the observation of the photographer quoted earlier [6], namely, "Composition is everything when it comes to photography".

Our work is *grosso modo* consistent with that of Obrador and co-workers [27], though even these authors found visual balance to be more significant to visual appeal of an image than correspondence to rule-of-thirds. The current preliminary results, particularly insofar as the inferences diverge from the conclusions of other published studies, imply the need for the development of a more sophisticated model of photographic composition than that of Liu *et al*. [26], one which incorporates additional compositional elements of recognized importance [5].

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