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Informational Dialogue with Van Gogh's Paintings

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Abstract

From the pioneering work by Birkhoff, several measures have been proposed to quantify the aesthetic content of art. After Bense's application of information theory to Birkhoff's ideas, the concept of informational aesthetics appears. In this paper, we analyze a selection of van Gogh's paintings using a set of informational aesthetic measures based on the entropy of the palette, the compressibility of the image, and an information channel to capture the basic structure of the painting. The values of these measures match fairly well against the different styles in van Gogh's work and allow a quantitative description of these periods. In addition, we present two new measures which quantify the information associated with both color and canvas regions and enable us to visualize the most salient colors and elements of a painting. We believe that informational aesthetic measures can contribute to discovering relevant characteristics of a painting or of a painter's style.

Categories and Subject Descriptors (according to ACM CCS): I.4.9 [Image Processing and Computer Vision]: Applications J.5 [Computer Applications]: Arts and Humanities

1. Introduction

Since the aesthetic measure proposed by George D. Birkhoff [Bir33], diverse measures have been presented to quantify the aesthetic values of a work of art. Among others, Bense [Ben69], Moles [Mol68], Nake [Nak74], and Machado and Cardoso [MC98] have introduced new concepts, mathematical tools, and algorithms to evaluate or to express the aesthetic experience (see also Greenfield's [Gre05] and Hoenig's [Hoe05] surveys). In line with these works, Rigau et al. [RFS07, RFS08] presented a set of measures based on both information theory and Kolmogorov complexity which enable the study of some informational aspects of a painting related to its palette and composition. The authors show how these measures allow the discrimination of different painting styles and to analyze compositional characteristics.

In this paper, after assuming a classification of van Gogh's paintings in six periods [Bro08], we propose an informational dialogue with van Gogh's artwork showing a significant consistency between the proposed aesthetic measures and period-styles, and also providing new tools to study the role of color in the painting composition. A quarter of van Gogh's paintings is analyzed using three tools: the entropy of the palette, the compressibility of the image, and an information channel to capture the basic structure of the painting. We also present two new measures which quantify the information associated with each color and region of a painting. These measures permit us to visualize the most informative or salient colors and elements (objects or regions) of an image. The main contribution of this paper is the proposal of a set of tools to help to study artist's work and discover relevant characteristics of a painting (or painter's style) which could go unnoticed by the observer.

This paper is organized as follows. Section 2 reviews the aesthetic measures which will be used in the rest of the paper. Section 3 studies the informational characteristics of a set of van Gogh's paintings in relation to different periods. Section 4 introduces two new measures to quantify the information associated with each color and region of a painting. Finally, Section 5 presents conclusions and future work.

2. Informational Aesthetic Measures

In this section, we focus our attention on the aesthetic measures presented in [RFS07, RFS08] and that will be used in Sections 3 and 4. In 1928, Birkhoff [Bir33] introduced the *aesthetic measure* of an object as the ratio between *order* and *complexity*. Later, in 1965, Bense [Ben69] and Moles [Mol68] interpreted Birkhoff's measure from an information-theoretic perspective. Nake [Nak74] conceived the computer as a *Universal Picture Generator* capable of "creating every possible picture out of a combination of available picture elements and colors." Machado and Cardoso [MC98] established that an aesthetic visual measure depends on the ratio between *image complexity* and *processing complexity*. Both are estimated using real-world compressors (JPEG and fractal, respectively). They consider that images that are simultaneously visually complex and easy to process are the images that have a higher aesthetic value. In [RFS08], Rigau et al. presented a set of measures that conceptualize the Birkhoff's aesthetic measure from an informational point of view. An initial group of global measures is based on Shannon entropy [CT91] and Kolmogorov complexity [LV97] and provides a set of scalar values associated with an image. A second group of compositional measures extends the previous ones in order to capture the structural information of an image.

From the creative process proposed by Bense, three basic concepts are considered: initial repertoire, palette used, and final color distribution. The initial repertoire is given by the basic states (in our case, a wide range of colors which we assume finite and discrete). The palette (selected repertoire) is the range of colors selected by the artist with a given probability distribution. From the palette, the artist distributes the colors on a physical support (canvas) obtaining the final product.

For a given color image $\mathcal{I}$ of N pixels, we use an sRGB color representation based on a repertoire of 256^3 colors ($\mathcal{X}_{\text{rgb}}$). Note that any other color system could be used. From the normalization of the intensity histogram of $\mathcal{X}_{\text{rgb}}$, the probability distribution of the random variable X_{rgb} is obtained, representing the *palette* of a painting. The range of $\mathcal{X}_{\text{rgb}}$ can be reduced using the luminance function Y_{709}, which is a measure of the density of luminous intensity of a pixel computed as a lineal combination of its RGB channels (we use the Rec. 709: $Y = 0.212671R + 0.715160G + 0.072169B$). In this case, the alphabet is represented by $\mathcal{X}_\ell = [0,255]$ and its corresponding random variable is denoted by X_ℓ.

2.1. Global Measures

The *entropy* $H(C)$ of a random variable C taking values c in $\mathcal{C}$ with distribution $p(c) = Pr[C = c]$ is defined by

$$H(C) = -\sum_{c\in\mathcal{C}} p(c)\log p(c), \tag{1}$$

where logarithms are taken in base 2 and entropy is expressed in bits. In this paper, the set $\mathcal{C}$ will stand for either $\mathcal{X}_{\text{rgb}}$ or $\mathcal{X}_\ell$ (i.e., C is X_{rgb} or X_ℓ, respectively). The palette entropy fulfills $0 \le H(C) \le \log|\mathcal{C}|$. The maximum entropy $H_{\max}$ for random variables X_{rgb} and X_ℓ is 24 and 8, respectively. While the palette entropy $H(C)$ can be interpreted as the pixel color uncertainty, $N \times H(C)$ represents the information content of an image.

Following Bense's proposal of using redundancy to measure *order* in an aesthetic object [Ben69], an aesthetic measure of an image (in particular, a painting) [RFS08] can be expressed as the *relative redundancy*:

$$M_B = \frac{H_{\max} - H(C)}{H_{\max}}. \tag{2}$$

Relative redundancy takes values in $[0,1]$ and expresses one aspect of the creative process: the selection of the palette by the artist. This measure only reflects color information but does not take into account the spatial distribution on canvas. This is considered by the next measures.

The *Kolmogorov complexity* $K(\mathcal{I})$ of an image $\mathcal{I}$ is the length of the shortest program to compute $\mathcal{I}$ on an appropriate universal computer [LV97]. It is the length of the ultimate compressed version and is machine-independent up to an additive constant. Due to the non-computability of K, real-world compressors (e.g., PNG or JPEG) are used to estimate it (i.e., the value of K is approximated by the size of the corresponding compressed file) [LCL*04].

From a Kolmogorov complexity perspective, the *order* in an image can be measured by the difference between the image size (obtained using a constant length code for each color) and its Kolmogorov complexity. The normalization of the order gives us the following aesthetic measure:

$$M_K = \frac{N \times H_{\max} - K(\mathcal{I})}{N \times H_{\max}}. \tag{3}$$

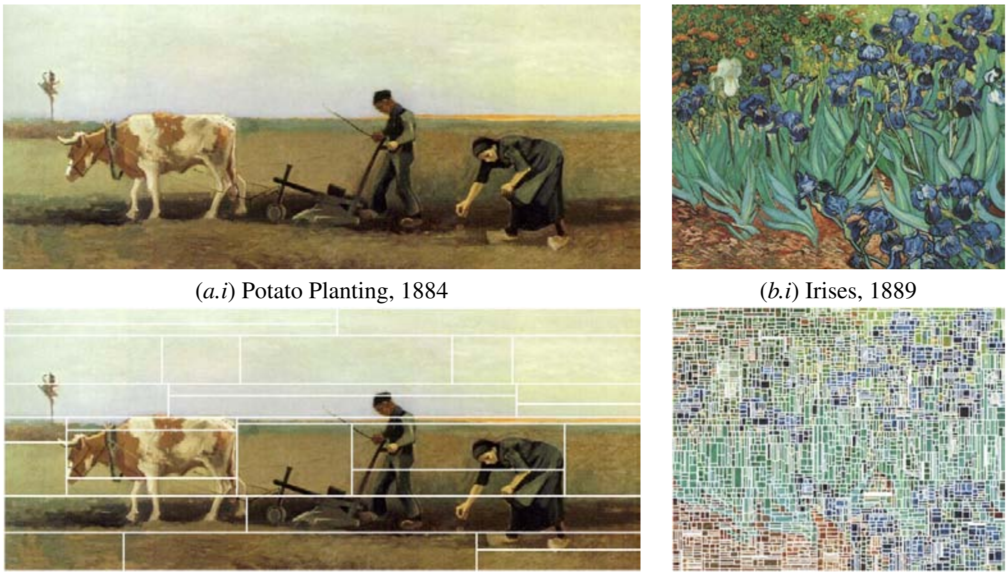
M_K takes values in $[0,1]$ and expresses the degree of order of the image without any prior knowledge of the palette (the higher the order of the image, the higher the compression ratio).

2.2. Creative Channel

The creative process described by Bense [Ben69] can be further understood as the realization of an information channel between the palette and the set of regions of the image [RFS08]. From this channel, an algorithm, which progressively partitions the image extracting all its information and revealing its structure, can be used.

The information channel $C \to R$ is defined between the random variables C (input) and R (output), which represent respectively the set of bins ($\mathcal{C}$) of the color histogram and the set of regions ($\mathcal{R}$) of this image. Given an image $\mathcal{I}$ of N pixels, where N_c is the frequency of bin c ($N = \sum_{c\in\mathcal{C}} N_c$) and N_r is the number of pixels of region r ($N = \sum_{r\in\mathcal{R}} N_r$), the three basic elements of this channel are

- The conditional probability matrix $p(R|C)$, which represents the transition probabilities from each bin of the histogram to the different regions of the image, is defined by $p(r|c) = \frac{N_{c,r}}{N_c}$, where $N_{c,r}$ is the frequency of bin c into the region r. Conditional probabilities fulfill $\forall c \in \mathcal{C}.\ \sum_{r\in\mathcal{R}} p(r|c) = 1$.



(*a.i*) Potato Planting, 1884 (*b.i*) Irises, 1889

(*a.ii*) $M_s^{-1}(0.25) = 29$ regions (*b.ii*) $M_s^{-1}(0.25) = 3{,}378$ regions

Figure 1: *(i) Two van Gogh paintings corresponding to (a) period 2 and (b) period 5, © 1996-2008 David Brooks. (ii) Binary-space partitions for a 25% mutual information gain.*

- The input distribution $p(C)$, which represents the probability of selecting each intensity bin c, is defined by $p(c) = \frac{N_c}{N}$.
- The output distribution $p(R)$, which represents the normalized area of each region r, is given by $p(r) = \frac{N_r}{N} = \sum_{c \in \mathcal{C}} p(c)p(r|c)$.

The *mutual information* between C and R is defined by

$$I(C,R) = \sum_{c \in \mathcal{C}} \sum_{r \in \mathcal{R}} p(c,r) \log \frac{p(c,r)}{p(c)p(r)} \tag{4}$$

and represents the *shared information* or *correlation* between C and R.

For a decomposition of image $\mathcal{I}$ in n regions, the *ratio of mutual information* is defined by

$$M_s(n) = \frac{I(C,R)}{H(C)}, \tag{5}$$

where $H(C)$ is the maximum value achievable for $I(C,R)$ (when each region coincides with a pixel) [RFS08]. The inverse function

$$M_s^{-1}\left(\frac{I(C,R)}{H(C)}\right) = n \tag{6}$$

gives us the number of regions obtained from a given mutual information ratio and can be interpreted as a measure of *image complexity*.

A greedy mutual-information-based algorithm can be used to split the image in regions with a quasi-homogeneous palette [RFS04]. The procedure takes the full image as the unique initial partition and progressively subdivides it according to the maximum mutual information gain for each partitioning step. The algorithm generates a partitioning tree for a given ratio of mutual information gain (5) or a predefined number of regions (6). This tree captures the structure and hierarchy of the image, and the mutual information gained in this decomposition process quantifies the capacity of an image to be ordered or the feasibility of decomposing it by an observer [RFS08]. In Fig. 1, we show two binary-space partitions obtained by a 25% mutual information gain and using the luminance channel (i.e., $C = X_\ell$). Observe how the different number of regions obtained for each painting captures its different compositional complexity.

3. Informational Analysis of Van Gogh's Periods

The work of van Gogh has been studied extensively [Lub96, Bro08]. We use here a quantitative new approach based on aesthetic measures to analyze the consistency of the results obtained with respect to the literature.

To study the evolution of van Gogh's style, we apply the informational aesthetic measures of Section 2 to a subset of paintings obtained from the excellent website *Vincent van Gogh Gallery* of David Brooks [Bro08], where the paintings are classified chronologically in six periods (see Table 1). The test set has been selected keeping approximately the same proportion for each period, discarding repetitions of compositions and covering all the categories: peasants, Japonaseries, portraits, landscapes, and still lifes. This set contains 219 paintings, representing a quarter of the total number of van Gogh's paintings.

In Table 1 we show the average value and standard deviation for the informational measures M_B (2), M_K (3), and M_s^{-1} (6) of the test set for each period. For practical purposes, we compute M_s^{-1} using luminance (X_ℓ). This is not a significant drawback as the eye is more sensitive to changes in luminance than in color and most of the information in a scene is contained in its luminance. In Fig. 2, we show a representative painting of each period according to the period-average of the aesthetic measures (Table 1). Next we analyze the van Gogh's periods in relation to informational aesthetic measures.

Stylistically, although his genius starts to appear in the first period, some works seem flat and the colors are not always used to their best effect [Bro08] (see Fig. 2.*a* and Fig. 5.*a*). Together with period 2 (Nuenen), his palette is dark and dull in tones (Fig. 2.*b*) but the works of period 2 reflect an important technical improvement as seen in his first great painting (see Fig. 5.*b*). The style of this epoch is captured by high values of M_B, corresponding to a limited palette, high values of M_K, meaning high degree of order and easy compression (few colors and tones, and simple compositions), and low values of M_s^{-1}, reflecting a basic compositional structure (see Table 1 and Fig. 1.*a*).

In Paris (period 3), van Gogh was influenced by Impressionism and Neo-impressionism, and his style underwent an important metamorphosis visualized by changes in the palette (from dark-hued to bright and vibrant colors), brushstroke (broken, broad, vigorous, and swirling), and subject (from peasants to Paris atmosphere). These changes also show his ongoing exploration of complementary color contrasts and a bolder style. Van Gogh wrote "I use color more arbitrarily so as to express myself more forcibly." As an example, the influence of Seurat's pointillism can be seen in Fig. 2.*c* and Fig. 5.*c*. The characteristics of this period are reflected in the values of the measures of Table 1 with a notable jump (decreasing M_B and M_K, and increasing M_s^{-1}) because of a richer palette and a more complex composition (more details, elements, and colors).

In Provence (period 4), van Gogh progressively improves his technique and uses characteristic and intense saturated colors (Fig. 2.*d* and Fig. 5.*d*). The work of this period reflects a synthesis of the two previous ones: Neuen and Paris. The aesthetic measures M_B and M_K decrease while M_s^{-1} increases slightly, following the tendency of the previous period.

In the short period of Saint-Rémy (period 5), van Gogh produces nice landscapes (Fig. 2.*e* and Fig. 5.*e*) characterizing his style by swirls. Impressionist artists sometimes use luminance to generate the sensation of motion and van Gogh used this in a more complex way. Van Gogh's ability to depict turbulence could be due to periods of prolonged psychotic agitation. Their patterns closely follow a Kolmogorov's statistical model of turbulence obtaining a high realism [ANB*08]. With respect to the behavior of the aesthetic measures, while M_B and M_K maintain similar values to the ones of the previous period, M_s^{-1} increases due to a higher compositional complexity. This fact is illustrated by the M_s^{-1} average for this period in contrast with the same measure for the previous periods (see Table 1 and Fig. 1.*b*).

In the final period (Auvers-sur-Oise), van Gogh could be moving into another new style [Bro08]. He is far from the style of the initial periods (Fig. 2.*f* and Fig. 5.*f*). The measures M_B and M_K achieve the lowest values reflecting their maximum distance with respect to the initial periods. On the other hand, M_s^{-1} continues reflecting a high compositional complexity.

It is interesting to observe the variation in the standard deviation of the aesthetic measures through the different periods. A higher deviation could mean more room for experimenting with palette and composition, while a lower variance would imply that the style is more defined. This matches the decrease in deviation when passing from period 3 (Paris) to period 4 (Arles). Observe also that in the M_s^{-1} measure (compositional complexity) the deviation jumps from the second to third period. This would agree with the fact that the artist would have already had a well defined composition style in the second period, but this would have been abandoned in the experimental Paris period. Lastly, let us remark that the increase in deviation in the last period in the palette measure M_B and the palette-compositional measure M_K would match with the hypothesis by some art critics that van Gogh could have been changing his style in this last period.

Fig. 3 shows the sequence of all selected paintings in ascending order according to the values of aesthetic measures. Each painting is depicted by a color bar which represents its period (1:yellow, 2:orange, 3:red, 4:green, 5:blue, 6:violet). In the M_B plot (Fig. 3.*a*), we can observe how yellow and orange colors (initial periods) mainly correspond to the highest values in comparison to the blue and violet colors (final periods) which tend to get the lowest values. The red color represents the transition period expressed by a range of middle values mixed with the other periods. Similar tendencies are shown for the M_K measure (Fig. 3.*b*). On the other hand, the compositional complexity expressed by M_s^{-1}, and calculated from three different mutual information ratios (0.15, 0.20, and 0.25), also shows a similar grouping. Thus, we can see how the lowest complexity corresponds mainly to the paintings of periods 1 and 2 and the highest complexity to the final periods. Observe that, for the plot of $M_s^{-1}(0.15)$ corresponding to a low level of captured information (Fig. 3.*c*), the differences in the periods appear clearer than in the other plots with more captured information (Fig. 3.*d* and Fig. 3.*e*). This is due to the fact that few partitions allow the capture of simpler composition in the first of van Gogh's periods, while the final periods need more partitions.

From the results obtained using the aesthetic measures we

Period			M_B		M_K		$M_s^{-1}(0.25)$	
Order	*Name*	*Years*	$\bar{x}$	$s(x)$	$\bar{x}$	$s(x)$	$\bar{x}$	$s(x)$
1	Earliest Paintings	1881-3	0.421	0.064	0.771	0.056	1072	984
2	Nuenen/Antwerp	1883-6	0.450	0.071	0.772	0.061	981	673
3	Paris	1886-8	0.378	0.061	0.704	0.073	1816	1005
4	Arles	1888-9	0.345	0.037	0.680	0.071	1823	935
5	Saint-Rémy	1889-90	0.338	0.026	0.690	0.048	2216	737
6	Auvers-sur-Oise	1890	0.324	0.033	0.677	0.072	2102	651

Table 1: *Average and standard deviation of the values of the informational aesthetic measures (M_B, M_K, and M_s^{-1}) for each van Gogh's period.*

(a) Fisherman's Wife on the Beach, 1882
(0.418, 0.759, 1264)

(b) Shepherd with a Flock of Sheep, 1884
(0.463, 0.739, 875)

(c) The Seine with the Pont de la Grande Jette, 1887
(0.385, 0.718, 1396)

(d) Sunset: Wheat Fields Near Arles, 1888
(0.345, 0.697, 1648)

(e) Olive Grove: Pale Blue Sky, 1889
(0.339, 0.593, 2456)

(f) Daubigny's Garden, 1890
(0.315, 0.714, 2375)

Figure 2: *A representative painting of each period is shown according to the average values of Table 1 (from period 1:(a) to 6:(f), © 1996-2008 David Brooks). The (M_B, M_K, $M_s^{-1}(0.25)$) values are indicated for each painting.*

can conclude that the six van Gogh periods could be further grouped in three: origins (periods 1-2), transition (period 3), and maturity (periods 4-6). The transition period (Paris), where van Gogh pursued art studies and met Impressionist painters, represents a break with his previous style and a changeover to new styles. We have seen how these three periods manifest themselves in the values of our measures, which are thus able to characterize the artistic evolution of the painter.

4. Color and Regional Information

In this section, we study how the information is distributed on the painting by computing the information associated with each color and region.

We now focus our attention on the mutual information between C and R, that expresses the degree of *dependence* or *correlation* between the set of color bins and the regions of the painting. From (4), mutual information can be expressed as

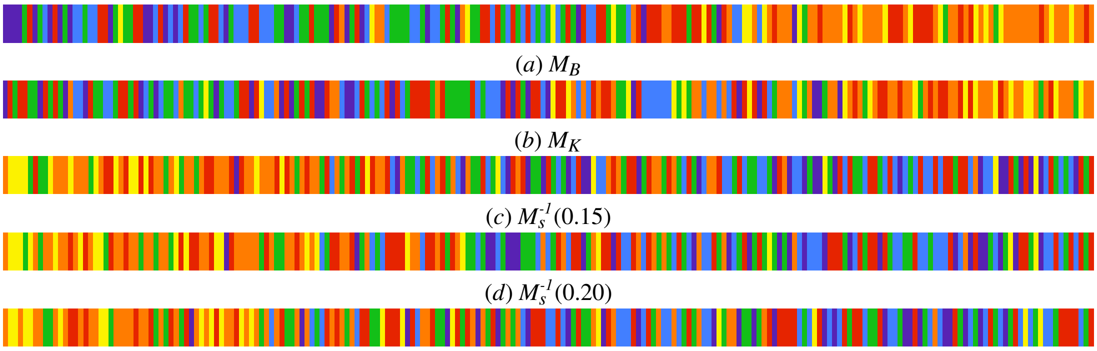
$$I(C,R) = \sum_{c\in\mathcal{C}} p(c) \sum_{r\in\mathcal{R}} p(r|c) \log \frac{p(r|c)}{p(r)} = \sum_{c\in\mathcal{C}} p(c) I(c,R), \quad (7)$$

where we define

$$I(c,R) = \sum_{r\in\mathcal{R}} p(r|c) \log \frac{p(r|c)}{p(r)} \quad (8)$$

as the *Color Mutual Information* (CMI), which gives us the degree of dependence between the color c and the regions of the painting, and is interpreted as a measure of the *information or saliency* associated with color c.

It is important to observe that $I(c,R)$ can be expressed as a Kullback-Leibler distance. This is defined between two



(a) M_B

(b) M_K

(c) $M_s^{-1}(0.15)$

(d) $M_s^{-1}(0.20)$

(e) $M_s^{-1}(0.25)$

Figure 3: *Plots of the sequence of test paintings in ascending order according to the values of aesthetic measures. Each painting is depicted by a color bar representing its period (1:yellow, 2:orange, 3:red, 4:green, 5:blue, 6:violet).* M_s^{-1} *has been computed for a 15, 20, and 25 percent of mutual information gain.*

probability distributions p and q as

$$KL(p|q) = \sum_{x \in \mathcal{X}} p(x) \log \frac{p(x)}{q(x)}, \tag{9}$$

and it is a divergence measure between the *true* probability distribution p and the *target* probability distribution q. Thus, $I(c,R) = KL(p(R|c)|p(R))$, where $p(R|c)$ (true p.d.) is the conditional probability distribution between c and the painting regions, and $p(R)$ is the marginal probability distribution of R, which in our case corresponds to the distribution of region areas (target p.d.). According to this, high values of CMI express a high dependence or correlation between a color and a given region, and identify the most relevant colors, that is, colors conveying more information. On the other hand, the lowest values correspond to the colors distributed uniformly in the painting.

Similarly, the information associated with a region can be defined from the inverted channel $R \to C$, so that R is the input and C the output. From the Bayes' theorem, $p(c,r) = p(c)p(r|c) = p(r)p(c|r)$, the mutual information (7) can be rewritten as

$$\begin{aligned} I(R,C) &= \sum_{r \in \mathcal{R}} p(r) \sum_{c \in \mathcal{C}} p(c|r) \log \frac{p(c|r)}{p(c)} \\ &= \sum_{r \in \mathcal{R}} p(r) I(r,C), \end{aligned} \tag{10}$$

where we define

$$I(r,C) = \sum_{c \in \mathcal{C}} p(c|r) \log \frac{p(c|r)}{p(c)} \tag{11}$$

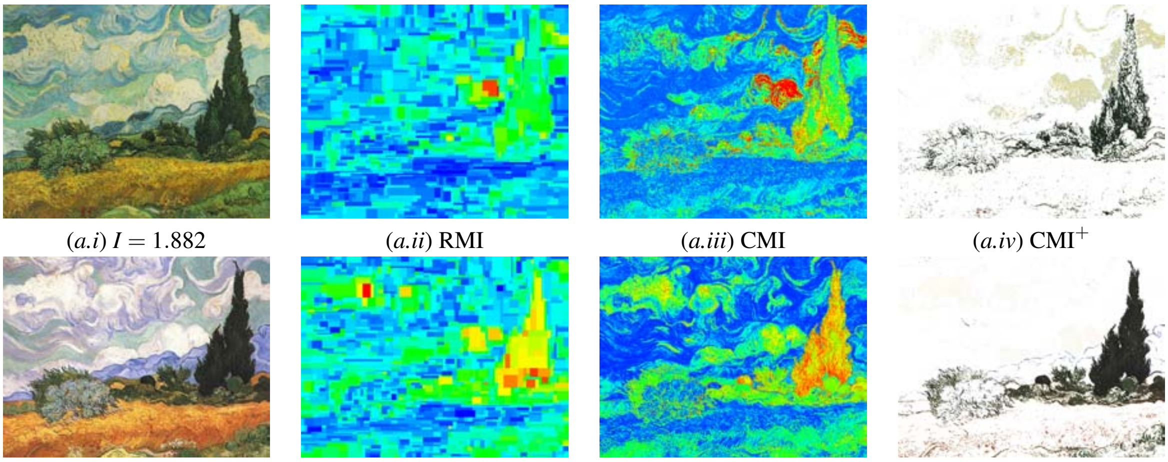
as the *Regional Mutual Information* (RMI), which represents the degree of correlation between the region r and the set of color bins, and can be interpreted as the information or saliency associated with region r. Analogous to CMI, low values of RMI correspond to regions that have an approximated representation of the palette (i.e., $p(C|r)$ is close to $p(C)$). On the other hand, high values correspond to regions that have few and exclusive colors.

In Fig. 4.*a*, we show a composition with a cypress which was an element associated with death that obsessed van Gogh. This work was painted in June 1889, after van Gogh's arrival at Saint-Rémy. Months before, he painted two variants of this composition. One of these is presented in Fig. 4.*b*. For both paintings shown, the information associated with each painting region (RMI) and with each color (CMI) is indicated. In the first case (Fig. 4.*ii*), a thermic scale (from blue to red) is used to represent the RMI values. In the second case (Fig. 4.*iii*), each pixel of the painting is visualized with the CMI value associated with its luminance. In addition, the images in Fig. 4.*iv* have been created depicting only the original pixels with CMI values in the upper half part of the CMI range (CMI$^+$). That is, only the most salient pixels of the painting are shown. Observe that, in spite of being the same composition, it is easy to see the informational differences between both paintings. For instance, the cypress is more salient in Fig. 4.*b* than in Fig. 4.*a* while some clouds are more salient in Fig. 4.*a*.

In Fig. 5, we show the CMI maps for a painting of each period representing different categories. Following the sequence of paintings, some of the most salient elements are the path and faces (Fig. 5.*a*), the lamp and most illuminated areas (Fig. 5.*b*), the eyes, mouth, and hat (Fig. 5.*c*), the petals of the sunflowers (Fig. 5.*d*), the moonlight and cypress (Fig. 5.*e*), and the cloud, soil, and house edges (Fig. 5.*f*).

5. Conclusions

In this paper we have considered informational aesthetic measures to study a subset of van Gogh's work. Although to study an artist's work from digital reproduction could be challenged as missing size, materials, relationship to viewer, and indeed physical existence, we believe that our measures



(*a.i*) $I = 1.882$ (*a.ii*) RMI (*a.iii*) CMI (*a.iv*) CMI^{+}

(*b.i*) $I = 1.937$ (*b.ii*) RMI (*b.iii*) CMI (*b.iv*) CMI^{+}

Figure 4: *(i) Two van Gogh's paintings of period 4: (a.i) Wheat Field with Cypresses at the Haute Galline Near Eygalieres, June, 1889, and (b.i) Wheat Field with Cypresses, September, 1889, © 1996-2008 David Brooks. (ii) Regional and (iii) color mutual information maps calculated using a 25% of mutual information gain. (iv) From the original painting, only the most salient pixels (its CMI is in the upper half range) have been depicted.*

can help to quantify the differences between the different styles and the evolution of a painter, and also show the way an artist used the colors of the palette to outline elements of a painting. Further work will be directed towards validating these measures against the work of other artists and also to analyze the interplay between the information conveyed by the three color channels and the luminance. This could help in keeping the most relevant information in color to gray conversion algorithms.

Acknowledgments

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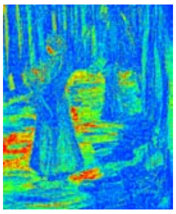
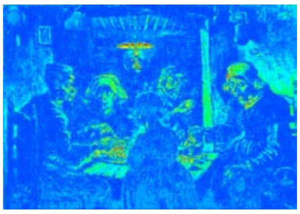
(*a.i*) Two Women in the Woods, 1882
(0.310, 0.650, 2020)

(*b.i*) The Potato Eaters, 1885
(0.575, 0.850, 1417)

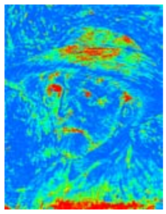
(*c.i*) Self-Portrait with Straw Hat, 1887
(0.295, 0.726, 1272)



(*a.ii*)



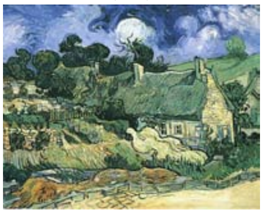
(*b.ii*)



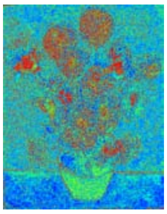
(*c.ii*)

(*d.i*) Vase with Fifteen Sunflowers, 1888
(0.349, 0.581, 2736)

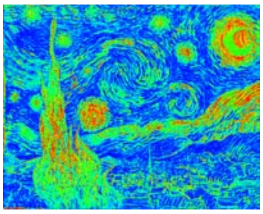
(*e.i*) Starry Night, 1889
(0.322, 0.594, 1758)



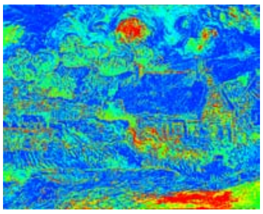
(*f.i*) Thatched Cottages at Cordeville, 1890
(0.312, 0.592, 2095)



(*d.ii*)



(*e.ii*)



(*f.ii*)

Figure 5: *(i) An outstanding painting of each period is shown (from period 1:(a) to 6:(f), © 1996-2008 David Brooks). The (M_B, M_K, $M_s^{-1}(0.25)$) values are indicated for each painting. (ii) Visualization of the mutual information associated with each color (CMI) using a thermic scale for each painting.*

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