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Computing the relevant colors that describe the color palette of paintings

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In this paper, we introduce an innovative parameter that allows us to evaluate the so-called "relevant colors" in a painting; in other words, the number of colors that would stand out for an observer when just glancing at a painting. These relevant colors allow us to characterize the color palette of a scene and, on this basis, those discernible colors that are colorimetrically different within the scene. We tried to carry out this characterization of the chromatic range of paints according to authors and styles. We used a collection of 4,266 paintings by 91 painters, from which we extracted various parameters that are exclusively colorimetric to characterize the range of colors. After this refinement of the set of selected colors, our algorithm obtained an average number of 18 relevant colors, which partially agreed with the total 11–15 basic color names usually found in other categorical color studies.

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1. INTRODUCTION

Millions of colors are usually accepted as being the order of magnitude of the number of discernible colors (NDC) in natural images [1]. It is obvious that an observer will not be able to differentiate such a great number of colors when he or she is looking at either a natural or an artificial scene. Although several color-naming approaches have been introduced to categorize color names and their corresponding color ranges [2–5], the link between the NDC and a more realistic estimation of these colors that are simultaneously perceived in a scene has not been fully studied and remains a conundrum.

There are very few studies that deal with the colorimetric characterization of the relevant colors that appear in a scene. From a graphic design point of view, it would be interesting to previously know the most adequate palette of colors for each scene, so algorithms have been designed to extract the so-called "color themes" [6,7]. Contrary to our proposal where the determination of the relevant colors algorithm is adapted to the chromatic content of each image, the algorithm proposed by Lin and Hanrahan [6] allows the automatic extraction of the thematic colors but with a limit of five per image. A similar extraction of perceptually plausible color themes from fabric color images [8] has also been tried. These authors used salience maps of textured samples to locate the dominant colors, thus allowing them to characterize the hue distribution in textile samples. But once again, the algorithm limits the extracted colors to just five (even the psychophysical experiment, which is designed to confirm the model, is limited to five extracted colors that the observers can choose as being the descriptive ones in each sample). Recently, Rafegas *et al.* [9] have proposed a color representation of images that achieves color contrast enhancement by using more than three channels, if required, and by maximizing the contrast with respect to the most representative color of each channel. The authors grouped red–green–blue (RGB) image colors by extracting local maxima of the histogram and defined the "color pivots" as the most predominant colors in the image. In a previous paper, we heuristically touched on the study of those colors that may attract visual attention during the observation of natural scenes, and we introduced the term "remarkable salient colors," which defined the discernible colors that were salient [10]. As the colors were salient, a plausible set of locations describing how observers tend to perceive a scene was not clearly connected with a presumably small fraction of the huge NDC.

Various spatial parameters, such as the fractal dimension, the power spectrum, entropy, and complexity, have been studied in depth in the computational analysis of paintings [11–13]. As far as color distribution and color ranges in paintings are concerned, Graham and Redies [14] point out that there is a lack of research in this field. Mureika [15] has studied the fractal dimension of paintings by Jackson Pollock and has established that the best system for studying the representation of color is CIELAB. Marchenko *et al.* [16] used the concepts of the temperature of colors, color contrast, and color palette to distinguish the differences between modern art and medieval art. Pinto *et al.* [17] have analyzed the influence of color temperature of the illuminants in the color gamut of paintings. Kim *et al.* [18] have found variations in the number of colors found in medieval art and in the rest of the posterior styles, with medieval art having the least number. Montagner *et al.* [19] have compared the color gamut found in a group of natural scenes and in 44 paintings by various painters. Their results show differences in the calculated slopes of the ellipses used to characterize the color gamut in the CIELAB color space. Nascimento *et al.* [20] have shown that the color gamuts painters use tends to coincide with the aesthetic preferences of the observers of the paintings. Lee *et al.* [21] have analyzed the chromatic contrast in large number of paintings and have found an increased diversity in the chromatic contrast in the last two centuries. Romero *et al.* [22] have compared the color gamuts of Renaissance and baroque painters and have found certain differences in the color volume, in the NDC, and in the average L* value, with these differences being greater for the Renaissance painters.

Color is always the fundamental aspect in execution of a painting, with each painter having his or her own characteristic color gamut. So, for example, painting styles such as impressionism or fauvism remain clearly in our minds due to the use of vivid colors of high clarity and saturation [23]. With other styles, such as the baroque, the colors used in a painting are fundamental to the composition. Nevertheless, various authors have shown that color is not sufficient in itself as a means of automatically categorizing a painting style [24,25]. In any case, as Graham and Field [26] have explained, "color plays a crucial role in the creation of art and a complete theory of how the regularities in art are related with the human visual system must, without any doubt, include color."

Computer vision algorithms have tried, from both the theoretical and practical points of views, to extract the colors that describe an image. The most commonly used have been based on clustering techniques such as k-means and fuzzy logic [27]; although the implementation of these algorithms is simple, they are not efficient because they need to somehow pre-estimate the number of clusters or colors from the start to function well. The analysis of maximum peaks of the frequency histograms for values that describe the chromatic characteristics of an image, such as hue, saturation, and value, has also been used to determine those pixels that have a greater relevance and associate them with significant regions in the color of the image [2,28]. The color quantization algorithms also attempt to extract the representatives of the colors of the image. However, generally speaking, these color quantization proposals are focused more on achieving the compression of the image without altering the quality and good reproduction in different devices [29,30]. It is also worth pointing out that algorithms known as "color-naming algorithms," which attempt to establish a discrete color characterization of the number of colors that appear in an image, are based on the "basic color term" concept introduced by Berlin and Kay [31]. From then on it has been found that, depending on the color lexicon, between 11 and 15 are the color names that are needed to define all of the linguistic color categories [32–34]. More recently, Griffin and Mylonas [35] have collected an impressive 20,000 unconstrained names for 600 color stimuli. By introducing a categorical measurement of the distance between two close colors, they have estimated that 27 categorically distinct regions can be fitted within the RGB color space. That number agrees with the use of only around 30 color names in spoken English [36] and the 50 distinct categorical territories in color space found earlier by Chapanis [37]. Nevertheless, as pointed out by Witzel and Gegenfurtner [38], "the origin of color categories. . . and observed patterns may result from the complex interaction of multiple constraints and determinants."

The aim of this study is to estimate a reliable color palette of a painting based on the novel notion of "relevant colors," which will be defined as the categorically discernible colors describing the chromatic diversity of that painting. The computational algorithm is tested with a public image data set that contains thousands of paintings from different painters and styles. The derived color palettes are also compared with a color-naming approach. Besides the average gamut found in all paintings, we also analyzed the NDC, the number of relevant colors (NRC), and the chromatic gamut ellipses.

2. METHODS

A. Image Data Set

We used a collection of 4,266 paintings by 91 painters from the public database of Khan *et al.* [25]. This collection is a good selection of the most relevant painters in Western art and covers painting styles from the Renaissance (15th and 16th centuries) to abstract expressionism (20th century). All of the images are publicly available on request at Ref. [39]. The images were used as they were included in the original database, which means that no additional calibration and/or post-processing was used. Other larger collections with public access have been used by other authors, such as Sigaki *et al.* [13]; nevertheless, we consider the collection we used to be sufficient for our aims.

B. Color Analysis

By using a digital image of a painting, we have been able to convert its RGB values into CIELAB values with the D65 illuminant. We thus obtained three values for every pixel in the image in a colorimetric representation (L^*, a^*, and b^* components), which is widely accepted and easily connects with the perceptive attributes and mechanisms of color vision. L^* represents lightness, a^* the relative red/green content, and b^* the relative yellow/blue content of the corresponding colors. Moreover, the a^* and b^* values are able to deduce the hue values, h^*, and the chroma values, C^*, related to the perceptive attributes of the same name. In previous papers, Kim *et al.* [18] and Lee *et al.* [21] worked directly with the RGB values of each pixel, thus avoiding the fact that color is an attribute of human vision and that its evaluation needs precise psychophysical measures, such as those used in a representation of color as in CIELAB. First, we averaged the L^*, a^*, and b^* values in each painting and then computed an ellipse that contains 95% of the pixels [19]. From this ellipse, we determined its orientation, area, and semi-axe ratio, which allowed us to obtain a good characterization of the distribution and gamut of colors in each painting. This is a good starting point for the future analysis of influence of painter and styles. We also determined the percentage of dark colors in each painting, considering those to be colors with an L^* value of less than 30. This fact is important because many painters have frequently used lightness and darkness to define their work, and some authors have even related the number of black pixels in different image subsections to homogeneity [40].

C. Computing the Relevant Colors of Paintings

As previously commented, although millions of colors are the order of magnitude of the color diversity in natural images, it is implausible that an observer would be able to differentiate such a huge number of colors in a complex image. Even observing complex images spatially and chromatically, observers will tend to count and/or describe only a small fraction of the huge number of potentially discernible colors. It should be clarified that the eye is capable of perceiving color changes in really complex scenarios with a high degree of resolution; Aldaba *et al.* [41] have shown that observers are able to discriminate between original and deliberately modified images with CIELAB color differences of about only 2.2 ΔE^*_{ab} units. However, this does not mean that observers will able to count all colors producing that ΔE^*_{ab} error. In a previous paper [10], we linked the term discernible colors and the salient areas in an image but only from a heuristic-based computational model. But how can we estimate the NRC that appear in or describe a color image?

First, as far as the NDC in a painting is concerned, this has been determined by using the method of Linhares *et al.* [1], which divides the CIELAB color space into cube units of different colors and counts those cubes that contain colors corresponding to the pixels in the image. The number obtained is the NDC in the painting, understanding as such those colors that are placed side by side in an isolated way and may be discriminated by the observer with normal color vision. This detail is worth pointing out because this situation is rarely found in a painting if we exclude some paintings with a very simple abstract composition with a very small number of geometric objects and a very uniform color (e.g., Piet Mondrian masterpieces). With this method, values that can be understood as "very" high (order of thousands) can be obtained; we can see in Fig. 1 an example of the chromatic diversity for one of the paintings containing as many as 18,829 discernible colors (compared to just 28 with our algorithm, as we will see further on). Therefore, we might wonder if the NDC thus obtained would correspond to that which an observer might determine with a simple visual inspection of a painting if we asked which were its main colors. Probably the observer would respond by indicating a reduced number of colors, less than one or two dozen. As we mentioned above, in a previous paper when we used natural images [10], we

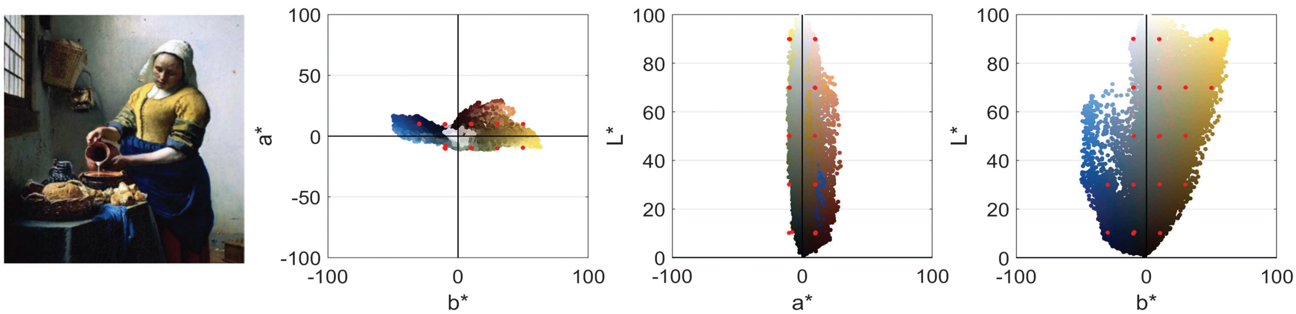

Fig. 1. Example of the distribution of discernible colors and the relevant colors (solid red dots) obtained in the CIELAB color space.

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Step 1.    Compute L*, a*, b*, and C* of each pixel (under D65 illuminant)
Step 2.    Divide CIELAB space in cubes of 20 ΔE*Lab units side
Step 3.    FOR each cube
Step 4.        Compute number of pixels inside the cube
Step 5.        Compute mean color of all the pixels inside the cube ('Cube Color')
Step 6.        IF the number of pixels inside the cube is greater that Thr of total number of pixels
Step 7.        THEN Cube Color is relevant
Step 8.        ELSE
Step 9.            IF (L*>80 or C*>percentile(50)) AND (Thr/8≤ Number of Pixels <Thr)
Step 10.           THEN  Cube Color is relevant
Step 11.           ELSE   Cube Color is not relevant
Step 12.   ENDFOR
Step 13.   Compute total number of relevant cube colors (i.e. Number of Relevant Colors)
Step 14.   Segmenting images in terms of Relevant Colors:
Step 15.   FOR each pixel in the image
Step 16.     IF the pixel is relevant (i.e. Cube Color is relevant)
Step 17.     THEN replace the pixel color by its corresponding 'Cube Color'
Step 18.     ELSE replace the pixel color by the closest 'Cube Color'
Step 19.   ENDFOR
Step 20.   Repeat all steps for every image
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Fig. 2. Pseudocode of the proposed algorithm to get the NRC. "Thr" means the threshold of 3% for the total pixels in the cube to consider the cube to be relevant (full details in the text).

touched on this problem, and we studied how the visual salience may be a filter that limits the number of colors on which an observer can fix his or her attention. The study, which was just computational, showed how the number of "significant" colors was 40%–55% less than the NDC according to the classic definition, which gives a much higher number of colors. Therefore, in this study, we developed a method that determines, at least colorimetrically, the number of colors that an observer would consider to be relevant in an image.

Second, we increased the dimensions of the cubes in which we divide the CIELAB color space, and we established a dimension while also setting as the parameter the minimum threshold of colors in each cube, i.e., the minimum percentage of colors compared to the total that should be within the cube. We have taken the division of the space into cubes of 20 units in every CIELAB direction as the criteria to follow, which allows us to divide the CIELAB space into approximately 125 cubes, setting a threshold of 3% for the total pixels in the cube to consider the cube to be relevant. We were aware that certain high chroma or high luminosity remained unconsidered as relevant colors. Milojevic *et al.* [42] found that the most saturated colors can act as predictors of how an observer would categorize the color distribution of natural objects. Thus, so we also considered cubes that had less than 3% total pixels, and at least 0.3% (3/8%) of the pixels included had the L^* value higher than 80, or a C^* value above the 50th percentile of the image. The colors considered as relevant colors are determined as by the average values of the colors of the pixels in each selected cube.

Once the relevant colors that appear in a painting have been determined, the algorithm assigns each pixel in the image with a relevant color (depending on the Euclidean distance between this relevant color and the color that should be assigned to the original pixel). The pseudocode in Fig. 2 summarizes all steps of the algorithm and at the end how to segment the image depending on its relevant colors, that is to say what we could understand to be the colors of the "palette" used by the painter.

D. Color Naming

We compared our results with those obtained by applying the classic color-naming algorithm used by Párraga *et al.* [43] (which is available online at Ref. [44]). Color naming predefines 11 basic colors [31], which correspond in English to the following terms and their associated RGB digital values: "Black" [0,0,0], "Blue" [0,0,1], "Brown" [0.5, 0.4, 0.25], "Grey" [0.5, 0.5, 0.5], "Green" [0,0,1], "Orange" [1, 0.8, 0], "Pink" [1, 0.5, 1], "Purple" [0,1,1], "Red" [0,0,1], "Yellow" [0,1,1], and "White" [1,1,1]. After applying a color-naming-based segmentation, we will compare the relevant colors found using our proposal with the fundamental colors derived from this color-naming approach.

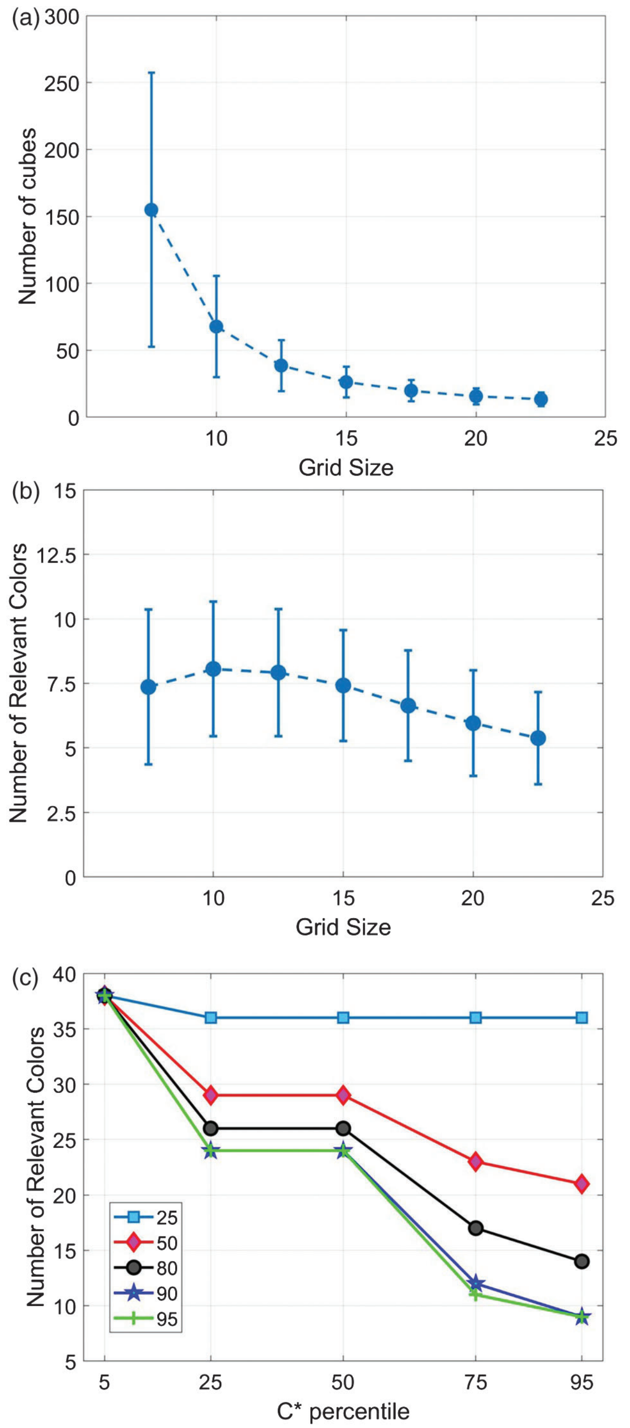

Fig. 3. (a) Total number of cubes containing a color and (b) NRC obtained for different grid sizes; (c) NRC derived for different L^* thresholds (as shown in the inset) and different C^* percentiles limiting the chroma values of each pixel.

3. RESULTS

A. Influence of the Cube Grid Size in the Computation of Relevant Colors

We first analyzed the influence of the CIELAB partitions (i.e., cube grid size) in the number of both discernible and relevant colors found. To do this, we selected different values of the cube grid size (from 10 to 40 CIELAB units) and checked how the total number of cubes containing a color and the NRC changes. The results suggest that the influence of the grid size in the number of non-empty cubes is negligible above 20–25, with a maximum of relevant colors found for grid sizes of 10–20 [see Figs. 3(a) and 3(b)]. Thus, we decided to choose 20 as the optimum grid size to be used in the following computations.

B. Influence of L^* and Chroma Values in the Computation of Relevant Colors

Once the value of 20 had been selected as the reference cube size for counting colors, we then analyzed the influence of the L^* and chroma values in the selection of the color palette of each painting. Figure 3(c) shows an example of the number of NRC obtained for different threshold values of L^* ($L^* < 25$, 50, 80, 90, or 95) according to the percentile selected, which limits the chroma value of each pixel (once the threshold value has been pre-set at 0.3% for the counting of the pixels within each cube).). For threshold values of $L^* = 25$ we can see how, independently of the value of the chroma, the NRC value is higher and practically the same as the cubes once the value of the 20 grid had been set (see the previous section regarding the grid values). On the other hand, we can see that percentiles for the chroma of between 25 and 50 do not modify the NRC, so we finally decided to select a threshold value for L^* of 80 and a percentile level of 50 for the chroma as the reference for the algorithm.

C. Color Statistical Descriptors

Figure 4 shows the frequency histogram for the different color descriptors in the analyzed paintings. Except, obviously, for the amount of dark pixels and the area of the discrimination ellipse obtained, all of the descriptors adjust to a Gaussian envelope. Chromaticity a^* and b^* distributions cluster around positive values, which are indicative of the large number of red, orange, and yellow colors in the image data set. The distribution of the angles of the longer axis of the fitted ellipses (with respect to the positive a^* component) shows most values to be around 50°–100°; an average value of 74° is obtained, which indicates that, on average, the major axis of the ellipses are rotated to the right of the b^* component. The distribution of the ratios between the major and minor axes of the ellipses varies from around 0.25 to 0.75, with an average of 0.45 with a relatively small standard deviation (SD) of 0.07. Finally, the distribution of the areas of the ellipses of the clusters is below 1×10^4 CIELAB units, with maximum values of around 3,000–4,000 CIELAB units.

Table 1 summarizes all of the colormetric parameters obtained. The NRC average for all of the paintings analyzed is 18 (with an SD of 6), significantly below the initial average 45 cubes obtained when counting those that contain a pixel (i.e., cubes with dimension 20 occupied with a pixel). As expected, the NRC is clearly below the 17,444 discernible colors (with an SD of 9,000) on average obtained. All of the chromaticity results (and the distributions of colors as shown in Fig. 5) are quite similar to the corresponding ones obtained by Montagner *et al.* [19], although our a^* is slightly higher on average (5.5 versus 1 for the paintings analyzed by those authors). Data of the fitted ellipses are also similar to earlier results with the exception of the distribution of the areas of the ellipses, which show much higher values than the values from Montagner *et al.* [19]. These differences may originate from the very different painting data sets used, indicating a much richer chromatic diversity in our case.

D. Color Palettes of Paintings Derived from Relevant Colors

Figure 6 shows examples of paintings in which we specify the NRC obtained for these paintings. This figure also shows the corresponding colors extracted that make up the palette for the

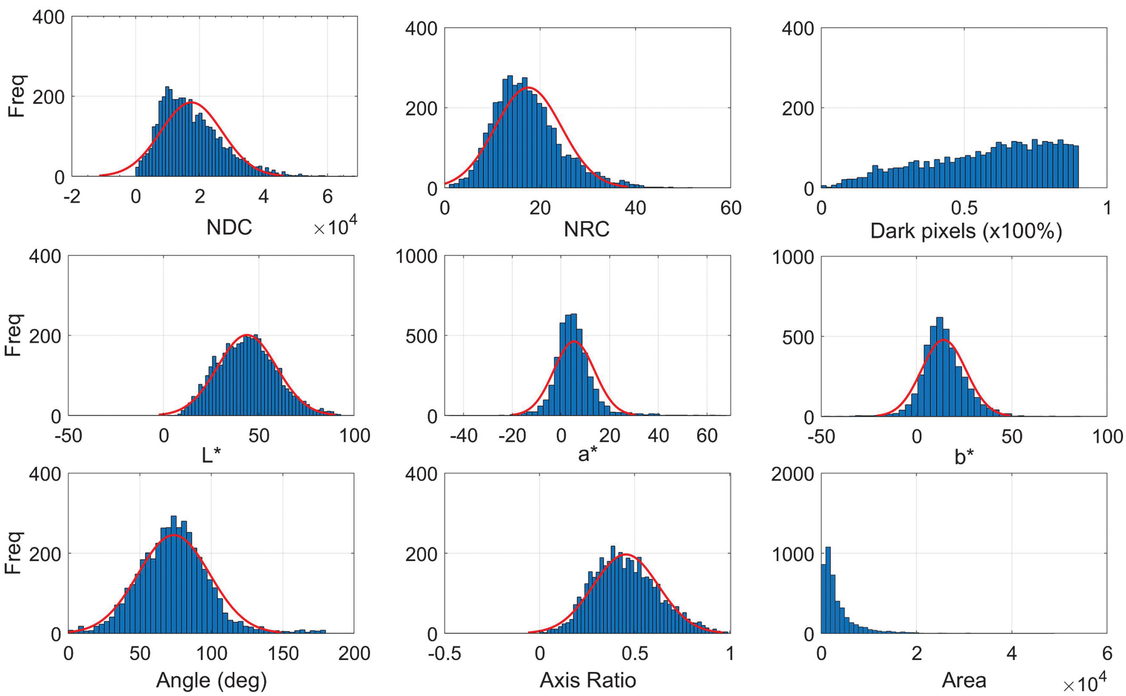

Fig. 4. Histogram of frequencies for all paintings describing (upper row) the NDC, the NRC, percentage of dark pixels; (middle row) color components L^*, a^*, and b^*; and (bottom row) angle, axis ratio, and area for all adjusted chromatic ellipses.

Table 1. Summary of the Colorimetric Parameters Analyzed

	NDC	NRC	Dark Pixels (%)	L^*	a^*	b^*	Angle (Deg)	Axis Ratio	Area
Mean	17444	18	64	44	5.5	14.5	74	0.45	3400
SD	9000	6	17	11	3.7	4.4	8	0.07	2500

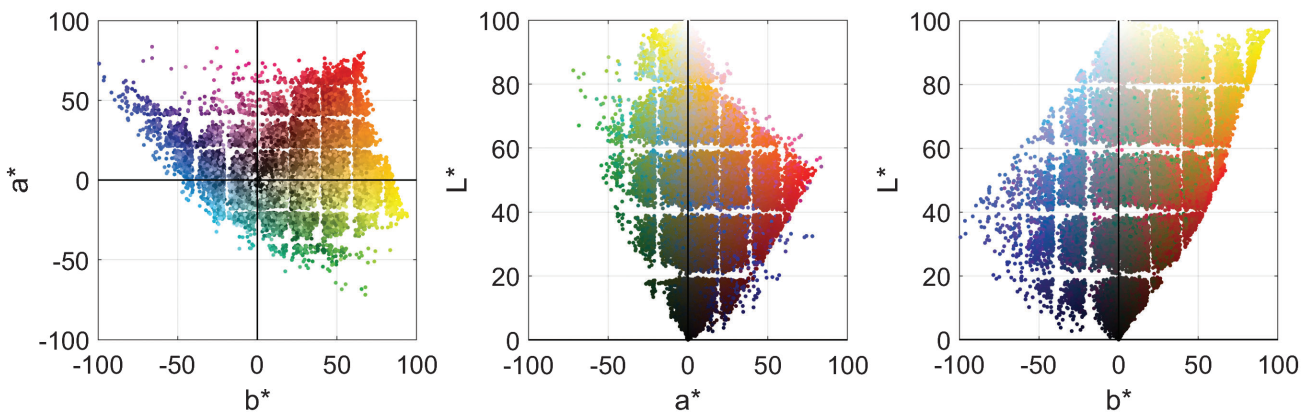

Fig. 5. Encompassed relevant colors and their corresponding L^*, a^*, and b^* color components for all paintings.

Fig. 6. Examples of segmentation according to the palette of relevant colors obtained. (Upper rows) *The Annunciation* (ca. 1432–1434) by Fra Angelico, who is an Italian painter of the early Renaissance (it contains 20 relevant colors according to the proposed algorithm); and (lower rows) *My Parents* (ca. 1977) by David Hockney, who is an English painter and contributor to the pop art movement (it contains 24 relevant colors).

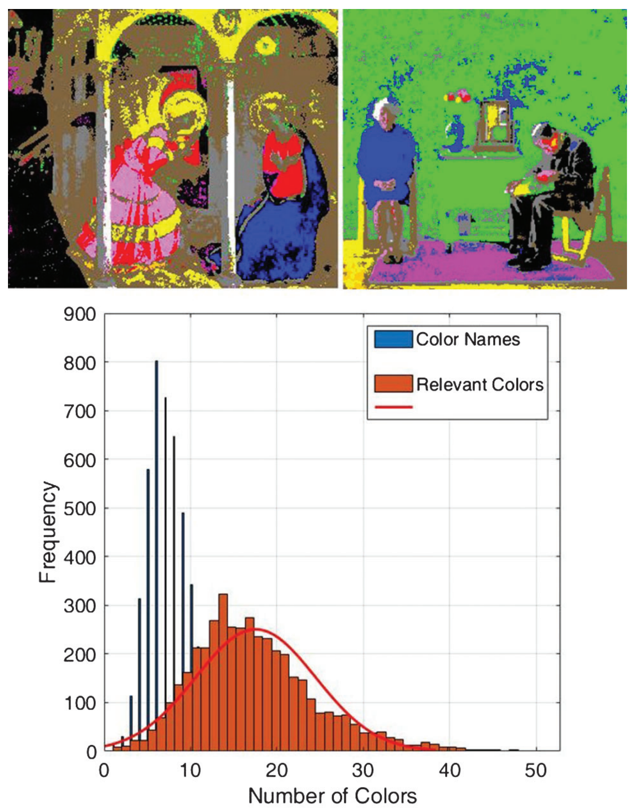

Fig. 7. (Upper plots) Examples of segmentation according to the color-naming algorithm (which obtains 10 and 9 colors for these painting), and (lower plot) comparison between the frequency histograms for the relevant colors and the number of colors selected via color naming for all of the database of Khan *et al.* [25].

painting. This palette allows us to assign the relevant color in the areas occupied by all of the pixels found within the cube. In a way, we have managed to achieve a colorimetric segmentation of the image in question as far as the discernible categorical colors that appear in the image are concerned. Although the results presented here suggest a potential application of the algorithm for image segmentation, this is not the main aim of this study. Yet, it could be argued that these categorical colors could not have subjective counterparts and are only related to purely colorimetric criteria.

E. Color-Naming Results

Figure 7 shows a comparison of the color-naming algorithm results and those we propose in this paper. As we have already mentioned, the average NRC obtained by our algorithm is 18, whereas the average number of colors obtained by using the color-naming algorithm for all of the paintings is 7.0 (±1.1 SD). Thus, the categorical number of color terms necessary to describe an image is below the NRC average. The great advantage of our method is that the relevant colors (the categorical discernible colors) derived are representative of the colors of each particular image, without being imposed and prefixed colors, as occurs with the color-naming algorithm (with 11 color categories being predefined for all of the images). Yu *et al.* [45] have tried to resolve this drawback by widening the number of colors to 39, showing that better results are obtained in applications related with segmentation for the classification of objects. This shows the limitations of color naming for this type of task; however, this topic is not the aim of this study.

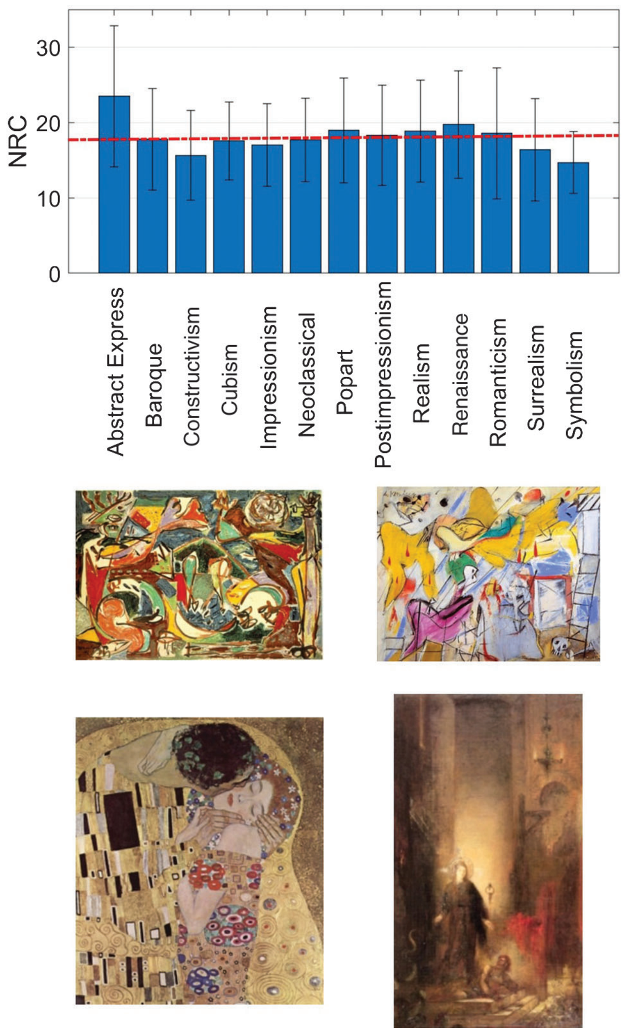

Fig. 8. Analysis by styles (the top two paintings are examples of abstract expressionism, and the ones below are examples of symbolism).

F. Painting Style Analysis

Figure 8 shows the analysis of the NRC obtained for each of the categories/styles into which the paintings in the Khan database [25] can be classified (according to the classification proposed by the authors). As shown, all of the styles are described by the NRC around the average of 18 obtained for them all from the database (the broken red line in this figure). There are only two styles where the NRC number obtained seems to be distant from the average values; however, the difference is slight. In the case of abstract expressionism, the NRC obtained is 23 (±9 SD) and therefore is higher than the average, not surprising when we consider that the paintings with this style are those of the works of Jackson Pollock and Willem de Kooning, which have a greater chromatic space complexity. As far as the symbolism style is concerned the opposite occurs, with 14 relevant colors being obtained (±SD), somewhat lower than the global average; examples of this painting style are the paintings by Gustave Moreau and Gustav Klimt, which would corroborate a greater chromatic simplicity in the artistic organization of the elements in their work. These results agree with the results of Kim *et al.* [18], who found that almost all artistic periods analyzed displayed a significant coincidence except the medieval period (i.e., the color palette in the medieval age is significantly different from the other periods and with a preference for a small number of selected colors). Nevertheless, that medieval art period is not adequately covered in the image data set used here.

4. DISCUSSION AND CONCLUSIONS

After the refinement introduced in the computation of the categorical discernible colors, we obtained an average number of 18 relevant colors that could be used to describe the color palettes of paintings. This represents a huge reduction in the number of colors in comparison with the initial average number of 17,444 discernible colors or the 43 threshold colors selected after a first constraint stage in the algorithm. The reduced number of only 18 relevant colors partially agrees with the total of 11–15 basic color names usually found in other categorical color studies [31,34]. Our method is able to derive different representative colors for each painting, is better adapted to the color content of every image, and does not need the introduction of predefined color categories. The key difference between our "relevant color" concept and the color-naming approach is not the absolute number but the way we adapt the NRC to the chromatic content of each painting. The colors behind every basic color name are always the same independent of the analyzed scene (i.e., color naming can select the number of names to describe an image but choosing those names and colors from a fixed color palette). Moreover, the algorithm can be used to extract the color palettes of paintings and then to automatically segment images according to their remarkable color content.

Our proposal for the determination of relevant colors present in a scene is close to being the result of a task-driven process (i.e., a top-down process) so that we are simulating how observers look toward those areas in a scene that are the most relevant, not only for being colorimetrically discernible but that also describe the palette (chromatic diversity) of the scene. New concepts about salient discernible colors and remarkable salient colors were introduced in an earlier paper [10] to be used to automatically create segmented images according to their salient chromatic diversity. The current proposal does not need to determine those areas that are visually salient in scene, and this will be the subject of future research. We plan to analyze the relationship between these salient areas, their number and extension, and the number of colors that really attracts the attention of an observer. Obviously, the NDC (as defined in early studies [1,19]) would not be the colors that an observer would use to describe an image in terms of its main colors. By looking into a picture of a painting it is far-fetched to imagine that an observer is able to differentiate (and to locate into the painting) the millions/thousands of colors predicted by the chromatic diversity of that painting. Although the study of the NDC has produced a large number of papers, so far little attention has been paid to the influence of the task of the observer regarding the determination of the number of colors. The majority of the theories of the recognition of patterns suggest that our visual system must have some type of specific mechanism for carrying out the visual analysis of a scene. To put it in another way, only once the basic components of visual structure or image have been processed can the structure or visual pattern be identified.

Regarding the NDC and the number of surfaces reliably discerned by an observer, Marín-Franch and Foster [46] have shown that this number of discernible surfaces is much less than the number associated to the discernible colors, at least in natural scenes. Nevertheless, this number of 7,300 that they estimate continues to be much higher than that which an observer would estimate for the relevant colors in a painting from a simple visual inspection. We have determined that the equivalent, in numbers, of these discernible surfaces that would be relevant colors is some 18 colors (or 40 if we relax the model and only consider those cubes that contain a pixel), which would be a plausible number to be considered by an observer to determine the palette that appears in the painting. If we take into account the relationship between the NDC and the expanded volume of the distribution of the colors found by Foster and Amano [47] (Eq. (15) in Ref. [47]), together with the 20 dimension for the discriminable cube used in our algorithm, we would obtain a comparable result to that predicted according to information theory. This is in agreement with our hypothesis of introducing the "relevant color" as a reduced number to describe the palette of a painter.

Various authors have explicitly expressed the opinion that there is a gap in the wide range of studies on the gamut of colors used in painting. Although it has been recognized that the use of color cannot be the only resource for identifying a style of painting within the history of art, it is clear that each painter has used a preferred palette of colors depending on the themes chosen, the materials used, the techniques employed, and the personal artistic preferences of the painter. A wider revision has recently been carried out by Van Geert and Wagemans [48] showing the complex and diffuse inter-relationship between the subjective measures associated with the aesthetic apperception of a painting and the various objective ways that try to quantify these visual aesthetics.

Do the results that we present in this paper presuppose that the concept of "relevant colors" should be linked to a categorical perception of color vision? Not necessarily, but recent neurophysiological studies [49,50] have identified the middle frontal gyrus in both cortex hemispheres as the human ventral V4 y VO1 areas that exhibit categorical clustering of neural representation of color and activation to identify color category and hue differences, which supports our hypothesis. Whether the color palettes derived here reproduce the subjective color terms used to describe a painting or their psychophysical counterparts is still an open question.

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