Autonomous Color Theme Extraction From Images Using Saliency

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ABSTRACT

Color theme (palette) is a collection of color swatches for representing or describing colors in a visual design or an image. Color palettes have broad applications such as serving as means in automatic/semi-automatic design of visual media, as measures in quantifying aesthetics of visual design, and as metrics in image retrieval, image enhancement, and color semantics. In this paper, we suggest an autonomous mechanism for extracting color palettes from an image. Our method is simple and fast, and it works on the notion of visual saliency. By using visual saliency, we extract the fine colors appearing in the foreground along with the various colors in the background regions of an image. Our method accounts for defining different numbers of colors in the palette as well as presenting the proportion of each color according to its visual conspicuity in a given image. This flexibility supports an interactive color palette which may facilitate the designer's color design task. As an application, we present how our extracted color palettes can be utilized as a color similarity metric to enhance the current color semantic based image retrieval techniques.

Keywords: Color theme, color palette, color design, saliency, automatic design, color semantics, color aesthetics, image retrieval.

1. INTRODUCTION

A color theme (palette) is a collection of salient color swatches which can represent or describe the choices of colors in an artwork or a design such as a graphic, fashion item, or interior. For instance, when designers are asked to design a piece such as a magazine cover, poster, or webpage, they often start by choosing a good image and then they extract the color palette from the image. The color palette is then used consistently through the design process. Designers usually choose a 3-color, 5-color, or occasionally a 7-color palette so that their designs are clean and sophisticated as opposed to busy and cluttered. In today's "Instagram" world, with the enormous number of digital images as well as design examples that can be downloaded from the Web, an automatic mechanism for extracting color palettes from images may facilitate the inspiration and creativity of designers. Applications of such an automatic mechanism, however, may also extend to other avenues of research in color quantization, transfer of the color mood of images, image retrieval based on colors, and image similarity metrics based on colors.

Traditionally, color palette extraction is performed by either utilizing a suite of well-known clustering techniques such as k-means and fuzzy c-means, or by quantizing color histograms of images (e.g. see [1–3]). The main problem with these tasks is that they often lead to extracting the mean colors of an image rather than colors appearing in the background and the foreground regions of an image. That is, they cannot effectively capture the various and yet fine colors that might occur in an artwork. Recently, Lin and Hanrahan [4] introduced a different solution *; a regression model trained on 1600 collected color palettes for 40 images from 160 human participants. Their model includes six types of features among which saliency is reported to be the main feature. Although their underlying images include several different painting styles and natural images, this approach, in general, may suffer from lack of spanning all the colors in a color space, as well as averaging and overfitting dilemmas. In contrast, in this paper, we suggest a more autonomous mechanism which is also based on the saliency map of a given image. The intuition of using saliency in our work has been shaped by consulting

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*Note that our work has been done separately and independently of Lin and Hanrahan. In fact, the time that we developed our approach was before their published work, and thus we had not any knowledge about their work. Nevertheless, in this paper we refer to their work to address the differences and similarities between our approach and their approach.

with professionals designers. Moreover, the autonomy of our approach provides an interactive color palette extraction for choosing K different colors in the color palette as well as visualizing the color proportions in the palette based on their levels of conspicuity in a given image. Such flexibility may facilitate the designer's color design task.

To extract K color swatches from a given image, our algorithm takes the image as an input, and computes its saliency map using a superposition of two saliency algorithms from [5] and [6]. The next step is to find the K choices of saliency pixels from this map, as follows: First, we find two colors (pixels) corresponding to the highest and the lowest saliency weights, as the first and the second choices of color swatches in the color palette. Then, for the k-th choice, we find a pixel with the furthest distance (a weighted distance in CIE$L^*a^*b^*$ color space based on saliency weight of this pixel) to the $k-1$ already selected colors in the color palette. In this way, we obtain a set of K saliency pixels. Our approach captures the dominant background color, the color corresponding to a highly localized, yet important feature, and a well-spaced distribution of colors between these limit points. The corresponding sRGB pixels of this set represent the choice of color swatches for the input image. This method is not trained on a set of images, and does not depend on any results from psychophysical experiments.

The flow of this paper is as follows: In Sec. 2, we briefly discuss prior work by reviewing approaches in color theme related topics. In Sec. 3, we explain our method as an autonomous mechanism of extracting colors for color palettes, independent of the kind of underlying saliency maps. In Sec. 4, we illustrate some results and discuss how using different kinds of saliency maps might be used for color palette extraction. In Sec. 5, we then discuss several applications of color palette extraction, mainly related to our prior work (which inspired us to tackle the color palette extraction problem). Finally, in Sec. 6, we conclude our work and suggest several next steps for future work.

2. RELATED WORK

As mentioned earlier, the recent work of Lin and Hanrahan [4] in developing a regression model to describe the way that people may extract color themes from images, is the closest work to our work. They note that saliency is one of the most important features in their model, because people often pay attention to the colors that "pop up". Our approach is also based on the notion of saliency in images shaped by consulting with professional designers. However, our approach is based on a closed-form solution, without the necessity of being trained on a set of images, and thus does not depend on any results from psychophysical experiments. Our approach supports the flexibility of changing the number of swatches in the color palette of a given image, as well as presenting their proportions (based on their visual conspicuity in the given image). These features provide an interactive color palette that may facilitate the designer's color design task.

Automatic/semi-automatic color design is a relatively new topic in color research. Luo [7] provides a survey in early stages of color science applications for product design. Tokumaru et al. [8] propose an automatic color design system which produces harmonized color combinations from a given pair of image and color as input of the user. For designing color harmony, they define a fuzzy model based on the notion of harmonious color templates by the color theorist Yutaka Matsuda [9]. Later, Cohen-Or at el. [10] utilized Matsuda's templates for color harmonization of images. Wang et al. [11] also apply Matsuda's concept of color harmony as well as several other guidelines from designers for color design in illustrative visualization. For image color theme enhancement, Wang et al. [12] suggest a system which takes as input an image and a color combination, and modifies the color composition of the given image accordingly. O'Donovan et al. [13] also suggest color theme enhancement of images based on aesthetically highly-rated color themes from Adobe Kuler online system [14] (also see [15] for their color theme aesthetics). Applying the notion of color semantics, Murry et al. [16] propose a system which transfers the color theme of a given image according to a color mood. These color moods are associations of linguistic concepts with color combinations pre-defined in the system's database. Finally, Jahanian et al. [17] suggest automatic color design for magazine covers based on several well-known geometric structures of color harmony as well as the notion of color semantics. In all of this prior work, extraction of colors from an image is performed through either color clustering or histogram quantization rather than by taking into account the notion of color saliency.

3. METHOD

The intuition behind using saliency in color palette extraction is that we often pay attention to the conspicuous regions or pixels in an image. A saliency map shows the level of conspicuity of pixels in an image. Figure 1 (b) illustrates a saliency map for the image in Fig. 1 (a). Note that in this saliency map, a higher lightness represents a higher conspicuity. To visualize the effectiveness of the saliency map in color palette extraction, we plot the colors of the image in Fig. 1 (a) in

Fig. 1 (c) and (d) in the CIE$L^*a^*b^*$ color space. In these 3D scatter plots, each color is represented with a cube. The size of each color cube is computed based on its corresponding saliency weight in the saliency map. That is, the more salient a pixel in the image is, the larger is the color cube for this pixel in the 3D scatter plot.

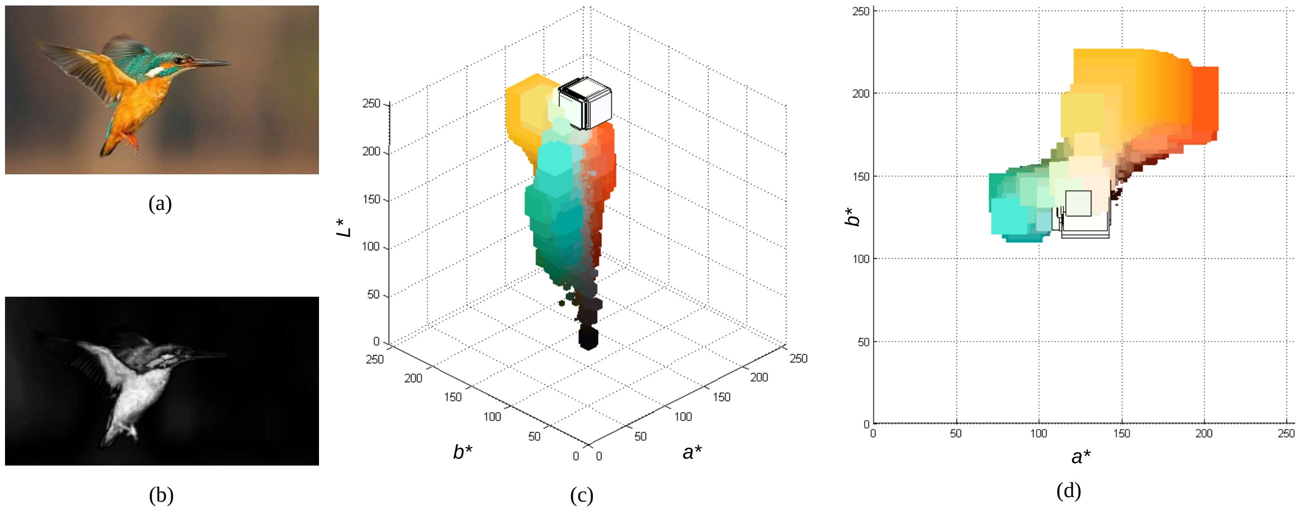


Figure 1. a) The original image. b) The saliency map of the image in (a), computed by using the techniques in [6]. Note that in the saliency map, a higher lightness represents a higher conspicuity for the corresponding pixels in the original image. c) and d) 3D scatter plots of the colors in the original image in the CIE$L^*a^*b^*$ color space, rendered from the $L^*a^*b^*$ viewport in (c), and the a^*b^* viewport in (d). In these 3D scatter plots, each color is represented by a cube. The size of each color cube is computed based on its corresponding saliency weight in the saliency map in (b). Photos courtesy of Prasad Hegde.

Note that we describe the problem in the CIE$L^*a^*b^*$, since among the color spaces, the CIE$L^*a^*b^*$ color space with a $D65$ reference white point is considered as a perceptually uniform space under $\Delta E \leq 2.3$, where ΔE denotes the distance between two colors, and 2.3 is the approximate value for one JND (Just Noticeable Difference) [18].

As the 3D scatter plot illustrates, the larger cubes are more representative of the conspicuous colors in the image, and thus good candidates to be included in the color palette of this image. On the other hand, we do not wish to select only the nearest neighbor color cubes. In fact, we prefer to select various colors to span the different conspicuous colors in the 3D scatter plot. This explanation of the problem can be formulated in an optimization problem where the cost function is defined for the maximum size of the color cubes and the furthest color distance between each pair of the color cubes in the CIE$L^*a^*b^*$. Given the largest possible cubes, we define the furthest color distance in Eq. 1.

More formally, assume that we wish to extract $K = 3$ color swatches from the image in Fig. 1 (a). Our first choice of color is the one with the highest saliency weight. Let denote this color pixel $\mathbf{p}_1$, a vector with L^*, a^*, and b^* color components in the first, second, and the third row, respectively. Although our second choice of color seems to be a pixel with the second highest saliency weight, only for this case —the second color in the palette—, we choose the one with the least saliency weight. This decision is made to capture the dominant background color, which presumably is not conspicuous to us, and yet very important in design. Let denote this color pixel $\mathbf{p}_2$. Our third choice of color, denoted as $\mathbf{p}_3$, is then the one with a well-spaced (perceptually furthest) distance to these limit pixels, $\mathbf{p}_1$ and $\mathbf{p}_2$. This pixel is computed according to the following equation:

$$\mathbf{p}_3^* = \underset{\mathbf{p}_3}{\operatorname{argmax}} \left(\min \{d(\mathbf{p}_3, \mathbf{p}_1), d(\mathbf{p}_3, \mathbf{p}_2)\}\right), \tag{1}$$

where we define $d(\mathbf{p}_i, \mathbf{p}_j)$ as a distance measure from pixel $\mathbf{p}_i$ to pixel $\mathbf{p}_j$ in the CIE$L^*a^*b^*$ space as

$$d(\mathbf{p}_i, \mathbf{p}_j) = w_{\mathbf{p}_i} [(\mathbf{p}_i - \mathbf{p}_j)^\top (\mathbf{p}_i - \mathbf{p}_j)]^{\frac{1}{4}}. \tag{2}$$

Note that in Eq. 3, $w_{\mathbf{p}_i}$ is the corresponding saliency weight of pixel $\mathbf{p}_i$. Thus, our distance is a weighted distance according to the saliency map of the given image. Although we explained our solution for the case of $K = 3$ color swatches in the color palette, one may compute as many color swatches as desired, in the same manner. For instance, for the k-th color swatch, given its saliency weight $w_{\mathbf{p}_k}$, the furthest distance is computed as the aggregate distance between this color and the rest of $k-1$ already selected colors.

In our implementation, we treat the optimization problem in Eq. 1 as a bipartite graph for the K nodes (here pixels $\mathbf{p}_1, \mathbf{p}_2, ..., \mathbf{p}_K$) with distances according to Eq. 3, and compute the cost of this graph using the Hungarian method [19] (also see [20]).

So far, we could extract the K color swatches with the above method. However, studies suggest that our eyes are more likely to discriminate the variations in hue than in lightness (e.g. see [21]). This observation also seems evident in the 3D scatter plot in Fig. 1 (d) with the a^*b^* viewport. That is, we wish to choose color cubes that are positioned around the exterior boundaries of the scatter plot. In order to take into account less sensitivity to the lightness variations, we modify Eq. 3 by multiplying the distance with a coefficient in matrix A for the lightness (the L^* component in any pixel):

$$d(\mathbf{p}_i, \mathbf{p}_j) = w_{\mathbf{p}_i}[(\mathbf{A}(\mathbf{p}_i - \mathbf{p}_j))^\top (\mathbf{A}(\mathbf{p}_i - \mathbf{p}_j))]^{\frac{1}{4}}, \tag{3}$$

where $\mathbf{A}$ is a 3×3 diagonal matrix with $a_{11} = l$ and $a_{22} = a_{33} = 1$. In our implementation, we heuristically choose $a_{11} = \frac{1}{3}$ (also see [21]). The results of our implementation are illustrated in Fig. 2 in the next section.

The method described in this section is independent of the kind of given saliency map. In fact, choices of different saliency maps may produce different results in the extracted color palette. In the next section, we discuss two kinds of saliency maps as well as a combined saliency map (a superposition of the two saliency maps). We then justify why we may prefer the results of the combined version.

4. RESULTS

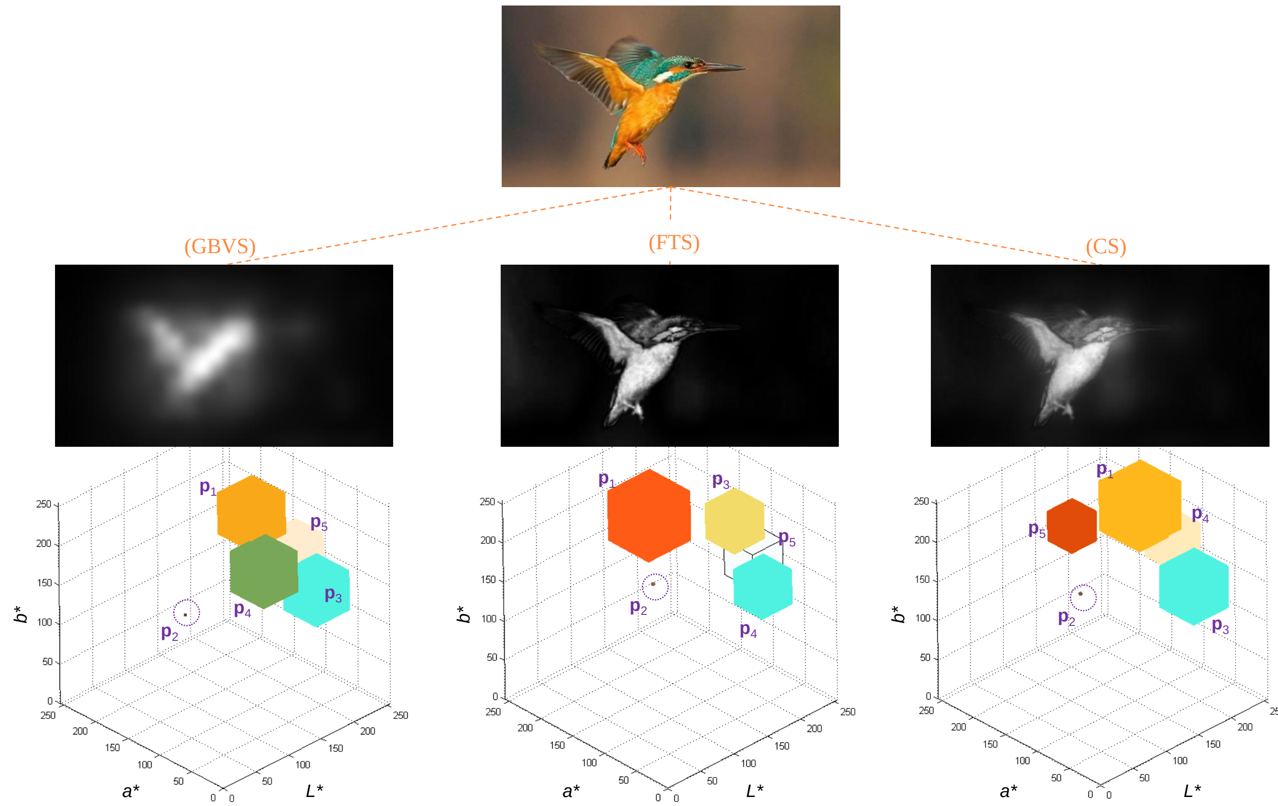
As mentioned in Sec. 3, our computational method is independent of the kind of saliency map corresponding to the input image. However, different saliency maps may produce different color palettes. Figure 2 illustrates the results of utilizing different saliency maps in our algorithm: a) the Graph-based saliency [5] (GBVS), b) the Frequency-tuned saliency [6] (FTS), and c) the combined (superimposed) version of the two other saliency maps (CS). One advantage of using saliency weights for color palette extraction is that we are then able to depict the priorities of color swatches in the color palette according to their corresponding saliency weights. Another advantage is that we may extract as many color swatches as desired. Accordingly, Fig. 2 shows the order of the extracted colors (see the labels next to each color cube) and their level of conspicuity (by means of the color cube sizes).

As Fig. 2 (a) illustrates, in contrast with FTS, using the GBVS results in a curse version of saliency. That is, while the conspicuous regions are detected, the fine details of those regions are not meant to be presented. This is because of the way that this kind of saliency is computed. The idea of GBVS is to compute visual saliency by applying the notion of graph theory in a bottom-up manner to construct maps (so called activation maps) as a means to store significant data according to some feature vectors of an image. Features are mainly based on color, intensity, orientation (of the textures) in the given image, and on human fixation in general [5]. GBVS then normalizes the activation maps by computing concentrated mass on maps to highlight significant locations. Our observations suggest that this saliency map is a good candidate for capturing the variety of colors in the background areas of an image.

Figure 2 (b) presents the results of utilizing FTS for computing the saliency map of the given image. This saliency performs well for capturing the fine details (regardless of the area) of the conspicuous regions. The reason for this is the fact that this algorithm computes the saliency weight of a pixel by accounting for how far this pixel is from the mean color of the entire image (the mean color is computed after some denoising such as low-pass filtering the image). Thus, the more a pixel differs from the mean color of the image, the more conspicuous this pixel will be. That is why this saliency algorithm is a good candidate to extract the variety of colors in the foreground areas of an image.

Figure 2 (c) illustrates the results of using a combined (i.e. superimposed) version of both GBVS and FTS maps. While the former accounts for the background regions, the latter captures the subtle pixels that “pop-up”. In this fashion, we can extract more diverse colors for the image’s color palette.

Our code is in Matlab and our experiments have been performed on a 64-bit PC machine with a 2-core 2.9GHz Intel processor and 8GB of RAM. For a 256×256 pixels image, the algorithm takes up to a few seconds to compute the results.



(a) (b) (c)

Figure 2. Results of our color palette extraction method using different kinds of saliency maps: a) GBVS [5], b) (FTS) [6], and c) a superimposed version of (b) and (c). Note that the extracted colors are visualized in the CIE$L^*a^*b^*$ color space in cubes. Since the size of these color cubes is based on their corresponding saliency weights, one may see the priories (levels of conspicuity) of these colors in their color palette. The labels ($\mathbf{p}_1, \mathbf{p}_2, ..., \mathbf{p}_5$) indicate the order in which the colors are extracted by using Eq. 1.

5. APPLICATIONS

5.1 Automatic Color Design

Design of a color palette —or which colors to choose to create a good design— is part of a designer's work and concern. In schools of design, students spend many years to learn general principles of design, and in particular, creation and usage of color palettes to convey emotions and ideas [22]. There are also resources (e.g. [14, 23–26]) that suggest color palettes to designers for the sake of inspiration and creativity. On the other hand, due to the emergence of automatic design of visual media for self-publishing (e.g. a magazine cover, poster, brochure, catalog, or webpage), the concept of color design is one which requires further investigation. As an example of automatic color design, we addressed some of the challenges in our prior work on automatic design of magazine covers (see [27] and [17]). We stated that the main challenge is how to determine a color palette that is aesthetically pleasing yet also contributes to the functionality of the design. For instance, when selecting colors for textual elements, how to assure the legibility and how to maintain the style consistency with the main cover image.

We note that one design principle elucidates making a contrast or a linkage between colors [28]. In regards, it is observed that in color design based on a given image, in prior work, all the methods are based on the distribution of the colors in the image rather than the conspicuity of the colors. However, it is also intuitive to design colors as a function of the extracted salient colors, in order to define a desired contrast or linkage. For more support of this idea, we demonstrate in the following section how utilizing salient color palette extraction may enhance the current color similarity metrics in automatic design and image retrieval, for recommendation of design examples and alternatives.

5.2 Color Similarity Metrics

Color similarity metrics are often defined and utilized for different applications such as image retrieval [3], color palette matching for images [20], and color theme enhancement [12] or transfer in images [16]. For instance, Solli and Lens [3] have defined a framework for image retrieval based on a set of given color combinations designed for conveying moods (color semantics). The notion of color semantics deals with how to relate sets of color combinations with color mood descriptors, for example, when a set of colors conveys a mood such as "nostalgic" or "elegant". One of the well-known spaces of color semantics belongs to Kobayashi's Color Image Scale [28, 29]. The framework defined by Solli and Lens is able to index a given image with Kobayahsi's color moods.

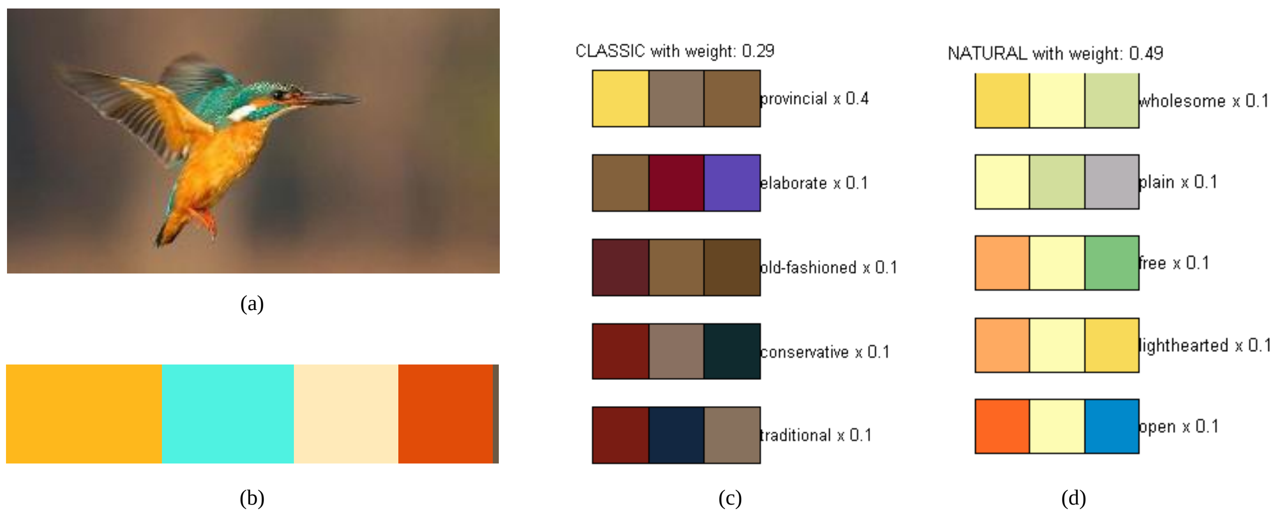


Figure 3. A comparison of results of color palette matching for a given image. a) The original image. b) The extracted 5-color palette for the original image. This color palette also represents the priorities (from left to right) and the proportions of the colors based on their visual saliency. c) and d) Results of the matching of color semantics for the original image by using the system in [17]. Note that for (c), we give the original image to the system, whereas for (d), we give the extracted color palette of the original image to the system. Color palettes and their associated semantics in (c) and (d) are from Kobayashi's Color Image Scale [28].

In our prior work, we have applied Kobayashi's color semantics for a recommendation system in automatic design of magazine covers, by utilizing Solli and Lens's framework (see [17, 30]). While in many cases this framework performs well in associating color semantics with images, it does not effectively match some images with the color combinations, which in turn, results in an ineffective association between these images and color semantics. The reason is that, in the original framework, the matching mechanism is based on matching the color histograms of the given image with the color combinations. As discussed earlier, histogram based matching is not often an effective approach in color design. One reason for this is that it may capture more colors occurring in the background (or non-salient parts) of an image rather than the foreground (conspicuous) regions. Figure 3 illustrates an example where the histogram based approach and the salient color palette extraction method (discussed in Sec. 3) are compared. Note that in the new approach (Fig. 3 (d)), we first extract the 5-color palette (Fig. 3 (b))from the original image, and then compute the color palette matching for this color palette with the previous approach.

6. DISCUSSION AND FUTURE WORK

Color palettes can sever important functionalities such as defining metrics for quantifying aesthetics of images and visual design, and can support means for automatic/semi-automatic design of visual media. In this paper, we presented a method for automatic extraction of color palettes from images. Our method is based on the notion of the saliency and provides an interactive color palette. That is, the designer can choose a desired number for colors and see the proportion of each color in the palette based on each color's visual conspicuity in a given image. Our method is simple, fast, and it works based on a closed-form solution which theoretically spans all the colors in a color space. To illustrate an example, we presented how our extracted color palettes can be utilized in an application of image retrieval. Specifically, we showed the effectiveness of our method in matching color palettes with a given image in inferring color moods and semantics of the image. In order to improve the current work, we suggest several steps as follows.

Although our method is independent of the kind of the saliency map, investigating different saliency techniques may improve the results. As discussed earlier, some saliency maps can capture the subtleties of the foreground regions and some are better candidates in accounting for the background colors. In some cases, however, current saliency techniques are ineffective or erroneous in detecting salient regions of an image. For instance, occurrence of noise in some parts of an image might be mistaken as conspicuity. Similarly, such shortcomings may affect our selection of colors in the color palette.

From another perspective, when color palettes are extracted to facilitate designers, color preference is another parameter to be taken into consideration. Choice of colors may vary from individual to individual and hence, an adaptive system should support such a demand. As an immediate step, we wish to investigate some psychophysical experiments in order to learn from designers in their choices of colors. It is valid to consider different scenarios where the designer may wish to extract different tones (e.g. dull or vivid) from a gradient of colors (either same or similar hues) appearing in an image. For instance, in the Kingfisher image (illustrated as the original image in this paper's figures), which tone of cyan in the feathers would serve a specific purpose in a visual design task?

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