Exploring the Use of Memory Colors for Image Enhancement

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ABSTRACT

Memory colors refer to those colors recalled in association with familiar objects. While some previous work introduces this concept to assist digital image enhancement, their basis, i.e., on-screen memory colors, are not appropriately investigated. In addition, the resulting adjustment methods developed are not evaluated from a perceptual view of point. In this paper, we first perform a context-free perceptual experiment to establish the overall distributions of screen memory colors for three pervasive objects. Then, we use a context-based experiment to locate the most representative memory colors; at the same time, we investigate the interactions of memory colors between different objects. Finally, we show a simple yet effective application using representative memory colors to enhance digital images. A user study is performed to evaluate the performance of our technique.

Keywords: Memory colors, crowd sourcing, color reproduction

1. INTRODUCTION

Memory Colors have been defined as "those colors that are recalled in association with familiar objects".[1] Several early psychophysical studies support that the majority of people associate an *ideal color* with an array of everyday objects (skin, grass, sky, plant, sand, and etc). Naturally these colors vary from person to person, but experiments have repeatedly shown that there are a few standard colors that most people recognize.[1–3]

Recently, several works have emerged using memory colors as a mechanism for segmentation and correction in the realm of digital images.[4–6] However, the fundamentals for all these techniques, i.e., the memory colors they rely on, are ambiguously vague. On one hand, some works[7,8] directly use memory colors determined by early psychophysical experiments,[1] which were performed using printed color chips under carefully controlled viewing conditions. However, the appropriateness of applying these colors for *digital images* under varying display conditions is not evaluated. On the other hand, some researchers[9,10] have experimented with on-screen memory colors, but enroll only a small number of participants under constant display conditions. Furthermore, none of previous work attended to the *interactions* of memory colors between different objects. For example, an largely unexplored question is: are the memory colors of concurrent sky and grass different from those when they appear separately?

In this paper, we investigate on-screen memory colors, which are suitable for image enhancement; and then show their use by a simple but effective color correction task. First, we perform an experiment to establish the *screen memory colors* of three pervasive objects in nature: skin, sky and grass. During the experiments the task of the participants is to select memory colors from color chips displayed on screen, which is analogous to the early *context-free* psychophysical study[1] where printed color chips are used. However, employing online crowd-sourcing tools, i.e., Amazon Mechanical Turk (MTurk), enables us to recruit a much larger group of observers under diverse display and viewing conditions. The resulting clusters on the color space form the overall distributions of screen memory colors.

Second, we perform a context-based experiment to locate *representative memory colors*. We manipulate the colors of skin, sky and grass within natural images to various candidate colors sampled from the previous distributions. Then we conduct a user study to evaluate the ratings of observers based on their color impression of these manipulated images. This way, the interaction of memory colors between different objects is measured. Also, the average ratings across all manipulated images reveal the preference for memory colors in the image context. The highest rated candidate colors are located as representative memory colors.

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Finally, we use a simple image enhancement task to show the effectiveness of representative memory colors. For uncorrected images with *memory regions*, i.e., regions of memory objects, we find increases in preference when these regions are shifted toward representative memory colors. The exceptions are those images captured (or processed) to deliberately include effects such as color cast for example, to convey a certain mood. In these cases association of memory colors is less appropriate. The major contributions of our work are as follows:

- A comprehensive crowd sourcing perceptual study demonstrating that distributions for context-free memory colors in uncontrolled environments are similar to those found in experiments with carefully controlled conditions.
- A subsequent context-aware study that locates representative memory colors. Also, it examines the interaction of memory colors, and the relative impact of different memory colors on human judgment of image quality.
- A technique that uses representative memory colors to reduce the three dimensional adjustment of image colors to a simple one dimensional adjustment. A validation study reveals the applicable cases for this method.

2. PREVIOUS WORK

The notion of memory colors dates back over several decades. Katz[11] asserts that human observers frequently exaggerate salient aspects of color, particularly if the object is associated with a specific label. Subsequent research[1–3,9] reveal that the typical color of an object becomes a component of our memory, and influences our perception of colors of this object. Complementary studies investigate the effects of manipulating color of known objects. Even an object of known color is illuminated in a manner that does not match the color identified with it, the perceptions of human observers are still influenced by those colors in their memory.[9,10,12,13]

Early psychophysical studies on memory colors[1–3,9] ask participants to select, from an assemblage of printed color chips, the one that they most associate with familiar objects. The recorded judgments are found to form clustered distributions, which implies, that although memory colors of different people are not identical, they are located in a compact common area. Yendrikhovskij et al.[14] ask observers how natural *digital color samples* look in an attempt to locate memory colors for grass, sky and skin, where Gaussian distributions of memory color areas are found. Recently, Moreno et al.[6] perform a psychophysical study to explore memory colors under various lighting conditions. However, all these studies above are performed under strictly controlled display and viewing conditions. Also, only a moderate number of participants are involved due to practical limitations. In this paper, we use crowd sourcing techniques to perform a more comprehensive investigation into memory colors across a large range of variations. The *interaction* between the colors of multiple memory objects are also explored.

A number of recent applications use memory colors as their basis. In image enhancement, several studies find that a subset of colors are representative of those that both the expert and the naive target when modifying and judging image quality.[7,8] Most notably, the colors of three *memory objects*, skin, sky and grass, are identified as principal ones. Images that are manipulated to place the color ranges of these objects into memory color regions are viewed more preferentially.[15,16] Nachlieli et al.[5] focus their effort on automatic skin color correction using existing models of skin colors. Rahtu et al.[17] use memory colors in automatic color constancy for grass, sky and foliage. Besides, memory colors are used in image segmentation[4,18] and illumination quality evaluation.[19,20] However, the memory colors these techniques rely on are based on previous psychophysical experiments, which are not necessarily appropriate for image editing applications. The performance of memory colors in these techniques are not evaluated from a perceptual point of view. In this paper, we target to investigate on-screen memory colors, in particular, *representative memory colors*, which are suitable for image enhancement. Also, we conduct a user study to evaluate the effectiveness of a proposed simple color correction technique using representative memory colors.

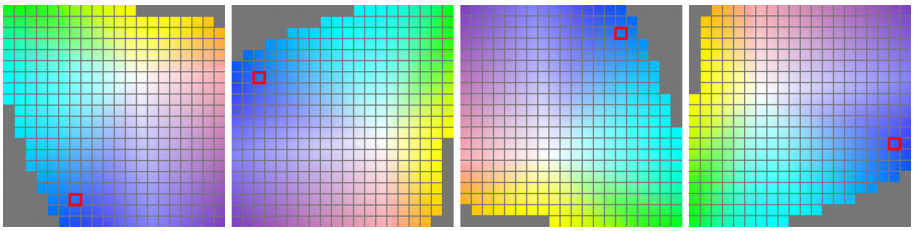

Figure 1. Examples of gamuts with different rotations displayed to MTurk workers. The red squares indicate the color chips picked by a worker to associate to the object "sky". These gamuts are individually presented to the subject at random.

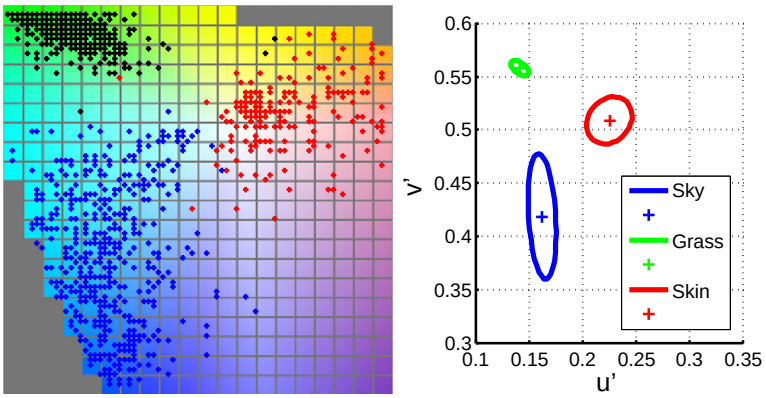

Figure 2. Left: Responses from MTurk workers: red crosses for skin, blue for sky, and black for grass. Right: $\sigma-$contours of fitted Gaussian distributions for three memory colors on $u'v'$ color space.

3. DISTRIBUTIONS OF MEMORY COLORS

We perform a visual perception experiment to investigate the overall distributions of memory colors on current display technology. It is an analogy to one original memory color experiment,[1] with stimuli adapted to screen display. We present digitized color chips (20x20 pixel^2) based on CIE 1960 UCS ($u'v'$) color gamut over a uniform neutral gray background. $u'v'$ values are converted to sRGB for display. No attempt is made to detect or adjust the participants monitor type, size or settings. This is our deliberate intention in order to involve a large range of variations in display and viewing conditions.

For each experimental trial, we show an object name, such as "sky", Mechanical Turk (MTurk) workers are then required to select the color chip they most associate with that object. Each object is presented four times with rotated gamuts. We investigate three objects: skin, sky, and grass. In the instruction, we specify our focus on "Caucasian skin" in this experiment. In total, we show each worker 3x4=12 questions. The order of objects and rotations of gamuts are randomized in order to minimize learning effects and bias. Figure 1 shows the examples of gamuts with four rotations and the color chips one worker picked for "sky". For one object, any selected colors which are inconsistent in four rotated gamuts are considered "invalid" and then discarded. In practice, if the magnitude of standard deviation of four colors are greater than 4 times the chip size, we consider these colors as inconsistent. If the four selected colors are consistent in rotated gamuts, we use the their average as the valid answer for the questioned object.

As a result, we collect 228 valid answers for skin, 519 for sky, and 568 for grass, as shown in the left diagram of Figure 2. These results establish the overall distributions of *screen memory colors*. We use three 2D Gaussian functions to approximate these elliptically shaped distributions (colors mapped onto $u'v'$ space under $D50$ illuminant). The Gaussian $\sigma-$contours are shown in the right plot of Figure 2. We compare our results (the Gaussian centers) with the memory colors from the previous psychophysical experiment[1] in Table 1. Due to the nature of crowd sourcing, a large range of participants, cultures, monitors, viewing conditions, and etc, are sampled. Despite all the potential variations in the stimuli, we find that the results are comparable with those from psychophysical experiments with controlled settings, which validates the usage of crowd sourcing techniques for color evaluation.

(u', v')	Sky	Grass	Skin
Bartleson et al.	0.151, 0.441	0.133, 0.499	0.221, 0.482
MTurk	0.162, 0.419	0.141, 0.558	0.225, 0.509

Table 1. Comparison between memory colors found by our experiment (Gaussian centers) and those by previous psychophysical experiments. The colors are converted to CIE UCS (u'v') color space.

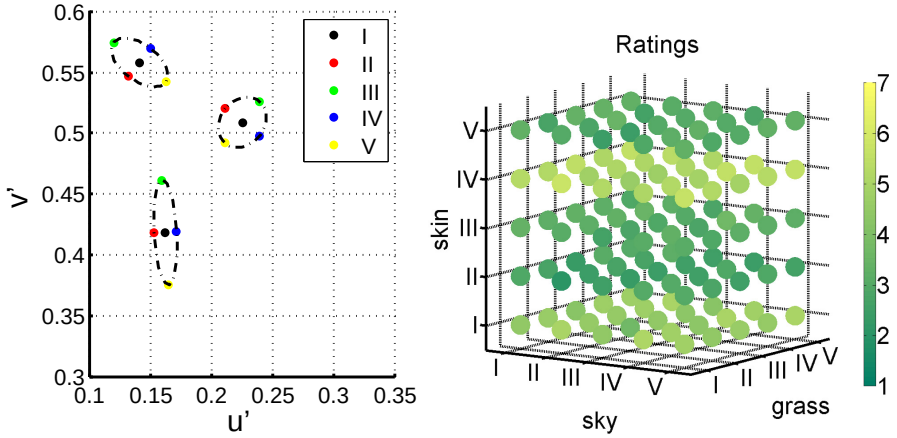

Figure 3. Left: Sampling ellipses for three memory objects and the candidate memory colors (5 for each object). Right: Illustration of $\overline{R}$, the overall average ratings for different combinations of candidate memory colors.

4. REPRESENTATIVE MEMORY COLORS

Given the overall distributions found in the previous experiment, our subsequent goal is to discover a few *representative memory colors*, which serve the best as "standard colors" in image enhancement techniques.[21] Theoretically, the fitted Gaussian centers represent the most selected colors, and thus represent a seemingly natural candidate. However, our previous experiment is performed in a *context-free setting*, which is suitable to sample a large number of candidate colors, but not necessarily appropriate to determine the best candidate colors for image enhancement, where image context is an important consideration.

Consequently, we perform a *context-based* experiment to locate representative memory colors. We take natural images that include regions of skin, sky and grass, and generate a set of stimuli by shifting the colors of individual regions toward a few candidate colors. Then, we ask viewers to rate these manipulated images, which contain different combinations of candidate colors. The ratings reveal humans' preferences for the joint distribution of three memory colors in the context of natural images. In this manner we locate the representative memory colors based on the preferences.

The candidate colors are sampled around the fitted Gaussian centers. This is analogous to a multi-scale searching scheme: we start with a coarse search, and then conduct a finer search based on the coarse results. Specifically, we sample 5 candidate colors around each Gaussian center. One of the candidate colors is exactly the Gaussian center, while the other four are sampled along a *sampling ellipse* (see the right plot of Figure 3). The orientation and the shape of sampling ellipse are identical to those of its overall Gaussian distribution. Each sampling ellipse is scaled so that three sampling ellipses have an equal area, $0.02^2\pi$ on u'v' color space. See the left plot in Figure 3.

When generating the stimuli, we shift the natural image, so that the colors of memory color regions are centered at 5 candidate colors defined above. For each natural image, we thus create $5^3 = 125$ combinations of manipulated colors. Five natural images, labeled as A, B, C, D, E, are used, which serve as various "contexts" in stimuli. We select natural images so that regions pertaining to three memory colors are roughly equal in size, which minimizes any affects due to the region size of the memory color. These regions are manually segmented. A subset of manipulated images is shown in Figure 4. See supplemental materials for all stimuli images.

As before, we use crowd sourcing to elicit the judgments on stimuli, while keeping results as general as possible. We ask MTurk workers to rate an images based only the quality of *the color reproduction*, ignoring

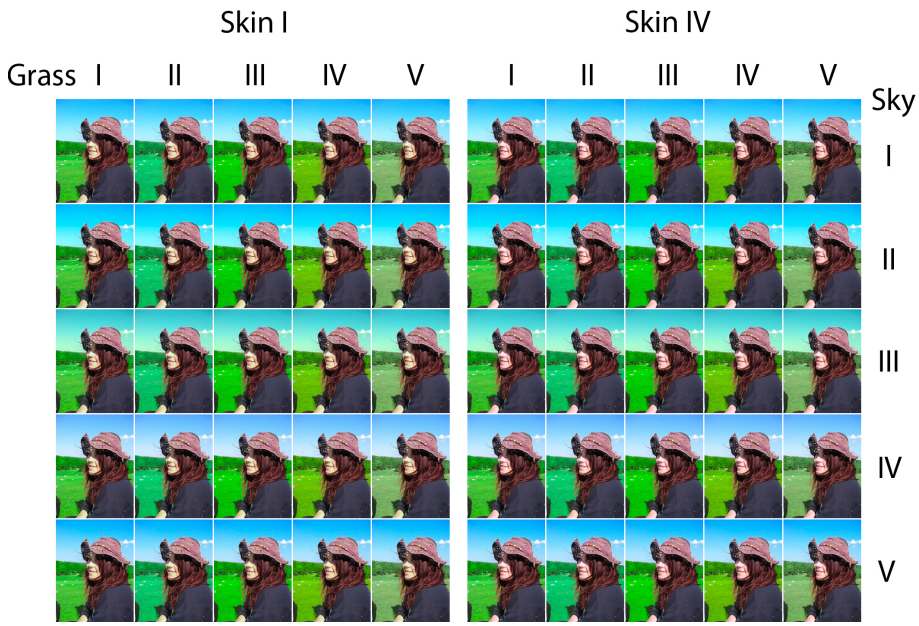

Figure 4. A subset of manipulated images based on a natural image. Due to the space limit, only two skin colors (I and IV) are shown, while five sky colors and five grass colors are demonstrated.

	R_A	R_B	R_C	R_D	R_E	$\overline{R}$
R_A	-	0.70	0.57	0.66	0.60	0.78
R_B	-	-	0.70	0.80	0.74	0.90
R_C	-	-	-	0.67	0.70	0.83
R_D	-	-	-	-	0.81	0.92
R_E	-	-	-	-	-	0.90

Table 2. Correlations between different R_m, where R_m records the average ratings for 125 manipulated versions of natural image m. The last column, $\overline{R}$, is the mean of five R_m, where $m \in \{A, B, C, D, E\}$.

all other image elements such as content, composition etc. Every worker rates 25 images out of 125x5=625 manipulated images, plus 3 test images to check the validity of the answer. The subset and the order of images are randomized to minimize bias. Ratings are given on a 7-point Likert scale from worst(1) to best(7).

We collect 422 valid responses from MTurk workers. We first test the consistency of subjects' ratings between different natural images. We use r_m^i to denote the average rating from all workers on a manipulated image, corresponding to memory color combination i ($i = 1, 2, ..125$) and natural image m ($m \in \{A, B, C, D, E\}$). For natural image m, the ratings for its 125 manipulations are represented by R_m, which is a 125x1 vector with $R_m(i) = r_m^i$. Table 2 shows the correlations between different R_m. The last column represents the mean of all R_m, where $\overline{R} = \frac{1}{5}\sum_{m\in\{A\sim E\}} R_m$. In Table 2, the generally high positive correlations demonstrate that, despite various image contexts, the ratings for different combinations of memory colors are rather consistent. Consequently, it is reasonable to use their mean, $\overline{R}$, to represent the overall average ratings. The right plot in Figure 3 illustrates $\overline{R}$ as a three-variable function, $\overline{R}(\xi_1, \xi_2, \xi_3)$. ξ_t represents the candidate colors of object t, where $t = 1(skin), 2(sky), 3(grass)$. We observe:

1. Skin color dominates the color preference. When present, skin color is the most crucial element in a scene, and the importance of other memory colors (grass and sky) falls off sharply.

2. No significant interaction between color memory objects is observed. The major variation of preference happens along the skin axis, while there are only small variations on its orthogonal plane (sky and grass).

	I	II	III	IV	V	(u',v')
Skin	4.59	2.71	3.14	**5.19**	3.06	**0.239, 0.497**
Sky	3.81	3.79	3.47	**3.83**	3.81	**0.171, 0.420**
Grass	3.78	3.60	3.66	3.81	**3.85**	**0.162, 0.542**

Table 3. The marginal ratings for three objects. The candidate color with the highest marginal rating for each object is highlighted in bold. Their corresponding chromatic values in u'v' are listed.

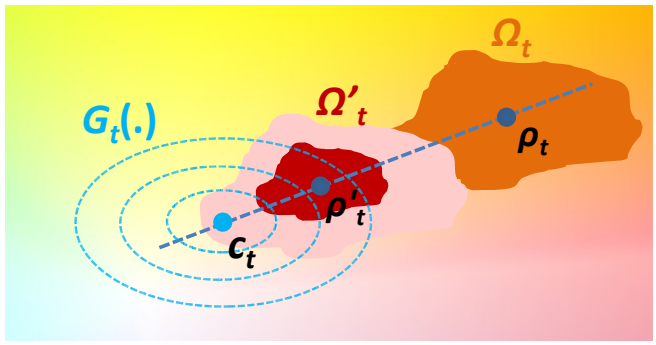

Figure 5. The original colors of pixels in Ω_t (orange) are shifted (pink) and then scaled (red), yielding the corrected Ω'_t. $\rho'_t = \rho_t + \beta\delta_t$ is the shifted centroid, $G_t(.)$ is the fitted Gaussian distribution of memory color t, centered at c_t.

The minimal interactions between the memory colors of different objects thus allow us to find the representative memory colors according to the *marginal ratings*. We define the marginal rating for a candidate color c ($I \sim V$) of memory object t ($t = 1, 2, 3$) as

$$R(t, c) = \frac{1}{25} \sum_{\xi_t = c} \overline{R}(\xi_1, \xi_2, \xi_3) \tag{1}$$

For example, the marginal rating on skin color II, $R(skin, II)$, is the average of all ratings on the plane $skin = II$ in the right plot of Figure. 3. The marginal ratings for three objects are listed in Table 3. We then define the memory color with highest marginal rating as the *representative memory color* for a certain object. Specifically, skin color IV, sky color IV, and grass color V are selected. Their chromatic values on u'v' are summarized in Table 3.

At this stage, we have used both context-free and context-based experiments to identify the overall distributions of screen memory colors, as well as, locate three representative memory colors. In next section, we demonstrate their usages in image enhancement through a simple yet effective application.

5. PRIOR-FREE IMAGE COLOR REPRODUCTION

Given a raw photo as input, people often seek a simple solution to making the component colors more pleasing. Color can be manipulated in many ways, the color domain with three degrees of freedom (two d.o.f without luminance) makes color reproduction a challenging task for non-expert users. Notably, the representative memory colors, which we locate using human preference via context-free and context-based experiments, serve as promising candidate "standards" for color reproduction. For images containing regions of memory objects, arbitrary color correction is converted to a one dimensional color shifting: moving colors of memory objects toward or against the representative memory color.

Our approach to adjusting images using memory colors is diagrammed in Figure 5, which shows colors in the u'v' space. We consider a memory object t in an image with colors in the region Ω_t, and seek to adjust the colors to be more similar to the experimentally determined memory color c_t for that object. In initial experiments we found that moving the distribution of colors Ω_t so that its centroid ρ_t coincides with c_t often results in unacceptably drastic changes to the image. We also found that in cases where the centroid of Ω_t is only moved towards c_t, objectionable results were obtained when many colors were pushed to the other side of c_t from ρ_t (i.e., to the lower left of Figure 5). To address these issues, we developed an adjustment that moves the colors

	couple	boy	gala	man	lady3	hat	maureen
β	1.0	0.5	0.5	0.7	1.0	0.5	0.5
	egg	teen	swing	lady2	music	lady1	sister
β	0.5	0.5	0.5	0.8	0.5	0.6	0.3
	boat	man2	baby1	wuhan	man1	funny	baby
β	0.5	0.4	0.5	0.4	0.5	0.1	0.5

Table 4. The settings of β for all results in Figure 6, in order of left-to-right and top-to-bottom.

of the memory object towards the memory color, and then scales the distribution of colors in the memory object so they do not extend too far from the memory color.

Specifically, taking an input image I containing memory objects, we first manually segment out the memory regions $\{\Omega_t\}$, where $t = 1, 2, ..$ representing different memory objects. Segmentation is accomplished using the color selection tool in Adobe Photoshop, yielding an alpha mask M_t (0.0∼1.0) associated with each Ω_t. For each pixel x, the greater $M_t(x)$ is, the more likely it belongs to Ω_t. Representing the centroid of Ω_t as

$$\rho_t = \frac{\sum_{x\in\Omega_t} I(x)M_t(x)}{\sum_{x\in\Omega_t} M_t(x)}, \tag{2}$$

the maximal amount of shifting for Ω_t is computed by

$$\delta_t = c_t - \rho_t, \tag{3}$$

where c_t is the representative memory color for object t. Then we are able to shift the colors within Ω_t towards c_t by an amount of $\beta\delta_t$, where $\beta \in [0.0, 1.0]$.

Following the shifting, a scaling s with respect to the shifted centroid of Ω_t is employed (see Figure 5). We will detail the computation of s later. To sum up, the overall color correction for each $x \in \Omega$ is computed as:

$$I^*(x) = \rho_t + \beta\delta_t + s \cdot (I(x) - \rho_t), \tag{4}$$

while the output corrected color $I'(x)$ is the alpha-blend of $I^*(x)$ and $I(x)$ according to mask $M_t(x)$.

To compute the scaling factor s, we fit a 2D Gaussian distribution $G_t(I)$ of memory color t, as we did in Section 3. But we use the refined representative color as the Gaussian center here. Then s is computed to satisfy that

$$\frac{1}{\sum_{x\in\Omega_t} M_t(x)} \sum_{x\in\Omega_t} M_t(x)G_t(I^*(x)) \geq w_t, \tag{5}$$

which guarantees that the average probability of corrected color being a memory color exceeds a threshold. Note that Eqn. 5 leads to a scaling with $s \leq 1.0$. The threshold $w_t = k_t\beta$, which indicates that a larger shifting β results in a higher threshold w_t, hence possibly more shrinkage (i.e., smaller s). The constant k_t is set to $0.96, 0.7, 0.7$ for skin, sky and grass respectively for all experiments.

5.1 Evaluation

We apply this simple color reproduction technique to 21 uncorrected images. All results are shown in Figure 6. In each image pair, the left is the uncorrected input, the right is the corrected version. Then only parameter we expose to users is the shifting amount β, while a preset $\beta = 0.5$ generally works well. The complete settings of β for all results in the paper are listed in Table 4. To evaluate these results, we perform a final crowd sourcing perceptual experiment again employing MTurk workers. This validation experiment proceeds by presenting each worker with a sequence of forced choice paired comparison trials to choose between uncorrected and corrected images. Each participant is asked to simply select the preferred alternative. Each worker is shown all 21 images plus 3 test images. We collected 161 valid responses.

We use the one-tailed $t-$test to compare the preferences for the uncorrected images and the corrected versions. If the corrected image is preferred against the original version at significance levels 0.05, we outline the corrected

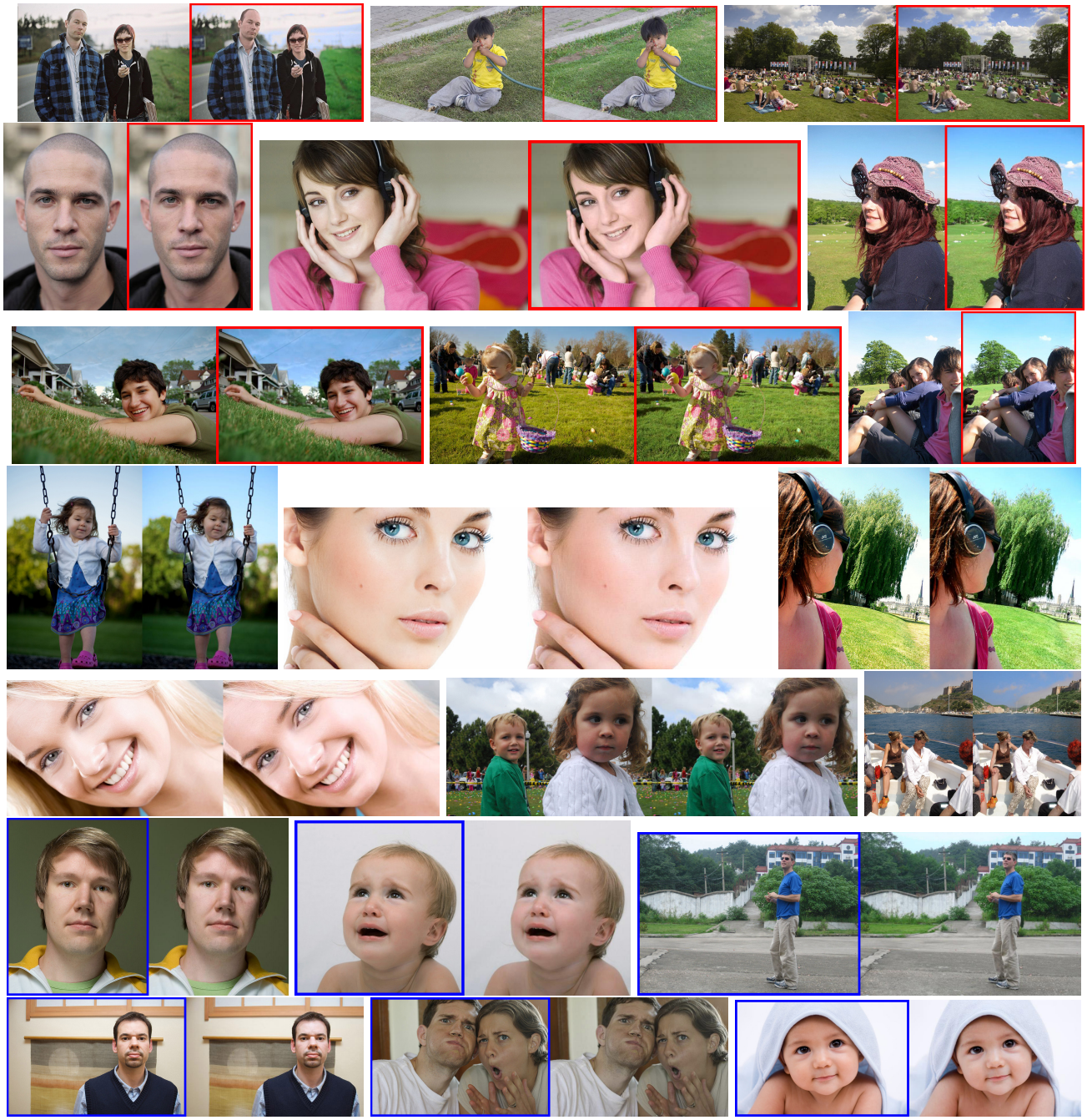

Figure 6. Results of color correction using representative memory colors. In each image pair, left is the original image, right is the corrected version. We use frames to outline the preferred versions if significance level 0.05 is achieved. We use red frames for preferred corrected versions, and use blue frames for preferred uncorrected versions. Two alternatives without frames are comparable to each other.

image with a red frame in Figure 6. If the uncorrected image is preferred at significance levels 0.05, we outline it with a blue frame. For two versions which are comparable (not significantly different in preference), we outline neither. All the results on user preference by $t-$test are shown in Figure 6.

The results show that shifting toward representative memory colors produce images that still appear natural and can, in many cases, be more visually pleasing. The representative memory colors serve as a nice "standard"

in the absence of an intended color cast or extra priors. The standard allows us to define a one (rather than three) dimensional adjustment for the user. The only parameter is a sliding position β between the original color and the representative color, which is straightforward even for novice users. Notably, the default setting $\beta = 0.5$ generally works well for a prior-free automatic image color reproduction.

Not surprisingly, we see both successful and failed example cases in this randomly selected pool of images. We notice two primary sources of errors. First, when the original images have intended color cast to convey a certain mood (e.g., first image on the last row in Figure 6), correction with memory colors loses this mood. Second, when there are additional factors that affect our expectations of the colors of memory regions the correction fails. For example, more yellowish skin colors than the memory color are expected with indoor incandescent lighting, and warmer skin colors than the memory color are expected for babies and children than for adults.

6. CONCLUSION

In this paper, a comprehensive investigation in on-screen memory colors and an application using them for image enhancement are presented. We first acquire distributions of three memory colors on screen using a context-free experiment, and then perform a context-based experiment to locate representative memory colors. We then propose a simple color reproduction technique guided by the representative memory colors. A user evaluation reveals a dichotomy of suitable and unsuitable cases to apply this technique. We also investigate the presence of interactions between memory colors, but find no significant interactions in our study.

While we recognize that color preferences are subjective, memory colors (esp., representative memory colors), are valuable in terms of providing a "neutral standard" for many image enhancement tasks, particularly when intended color casts or styles are not desired. We chose skin, sky and grass for this study as these regions often feature more prominently in natural images, in the future work we would like to include more objects, such as red-brick, soil and sand. Some direct applications are expected, e.g., simple color correction controls for off-the-shelf digital cameras and smart phones.

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