A Home Décor expert in your camera

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Abstract

We present a method to give color advice for Home Décor using images of room finishes, such as paint, flooring, or textiles, taken with uncalibrated cameras. Due to variations in color rendering across devices, an object imaged with different cameras will have different color values. Color information can still be accurately retrieved from uncalibrated images taken under uncontrolled lighting conditions with an unknown device and no access to raw data, when a limited number of known reference colors are available in the scene.

We demonstrate that the color of any object can be corrected using a number of calibration targets. A colored object is imaged with an appropriate calibration target in the scene. This target is extracted and its color values are used to compute a color correction transform that is applied to the entire image. Our system finds the closest match of the imaged object to a database of color coordinated paints. We can then supply the users with the appropriate color coordinates. Our results were validated by a Home Décor expert.

Introduction

Digital cameras have never been so common, compact, and affordable. With their integration into cell phones, most of us walk around with a camera at hand at all times. Images can be useful while shopping and it would be very convenient to simply send an image - over the internet or via MMS - and get expert advice in return for anything from makeup shade [7] to Home Décor.

Despite the ease of taking pictures, objective color assessment remains an issue, especially with the low quality of devices generally integrated into cell phones. The same scene imaged with different devices can result in quite different pixel values due to imperfect illuminant compensation and variable camera characteristics. It is impossible to accurately assign a color from a digital image, unless the camera has been previously calibrated.

Color properties of objects are fully characterized by their reflectance spectra, i.e. the percentage of light reflected by the object's surface at each wavelength and incident angle. However, in many applications it is sufficient to only retrieve tristimulus values, which can be achieved using an RGB camera or scanner [4, 13].

Our method only requires a calibrated target to be present in the scene, which is an inexpensive alternative to the use of calibrated devices. The object of interest is imaged together with a reference target, which allows color correcting images independently of the imaging device and illuminant. The extracted calibration target values allow computing a color correction matrix that is scene and camera dependent. This transform is applied to the entire image. The system relies on the assumption that any camera output color image encoding is sRGB [1]. Figure 1 shows an image of a sample and calibration target, before and after color correction.

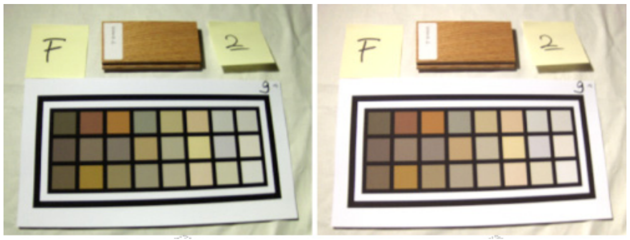

Figure 1. *An object is imaged with a calibration target used for the color correction of the object color. The left and right images are the uncorrected and corrected images, respectively*

Previous work [8] demonstrated the feasibility of this method for retrieving skin color information from a single digital picture taken with an unknown, casually posed consumer camera and under unknown lighting conditions, using solely a calibrated reference target representative of skin tones present in the scene. In the current paper, we investigate the possibility of adapting the method to wider ranges of hues in order to assess the color of virtually any object. We demonstrate the feasibility for Home Décor applications. The system is fed with an image of an interior color to be coordinated, such as textiles or wall coverings. We do not automatically create color harmonies, which is a difficult subjective task. Rather we use an existing database of color coordinated palettes, designed by an interior designer, in which we find the best color palette complementing the object's color. The color corrected object pixels are extracted, their values converted to CIECAM02 and compared against a database of paint samples to return the closest match. The system then returns a set of paints that complement the closest match and object colors. A Home Décor expert, a professional interior designer, graded the results as very good.

State of the art

The irradiance falling on a sensor is proportional to the product of $E(\mathbf{x},\lambda)$, the spectral power distribution of the illuminant, with $S(\mathbf{x},\lambda)$, the reflectance spectra of the object. The camera response $\rho_i(\mathbf{x})$ of the ith sensor $R_i(\lambda)$ at spatial position $\mathbf{x} = (x,y)$ can be modeled as

$$\rho_i(\mathbf{x}) = \mathbf{s}(\mathbf{x},\lambda)^T \cdot diag(\mathbf{e}(\mathbf{x},\lambda)) \cdot \mathbf{r}_i(\lambda), \ \ i = 1:n, \tag{1}$$

where the vectors $\mathbf{s}(\mathbf{x},\lambda)$, $\mathbf{r}_i(\lambda)$, and $\mathbf{e}(\mathbf{x},\lambda)$ are, respectively, $S(\mathbf{x},\lambda)$, $R_i(\lambda)$, and $E(\mathbf{x},\lambda)$ represented by 31 samples taken over the visible spectral range [11]. $diag(\mathbf{e}(\mathbf{x},\lambda))$ is a 31×31 matrix with the vector entries $e_i(\mathbf{x},\lambda)$ on its diagonal and n is the number of channels of the imaging device.

It is not a trivial task to retrieve reflectance values from cam-

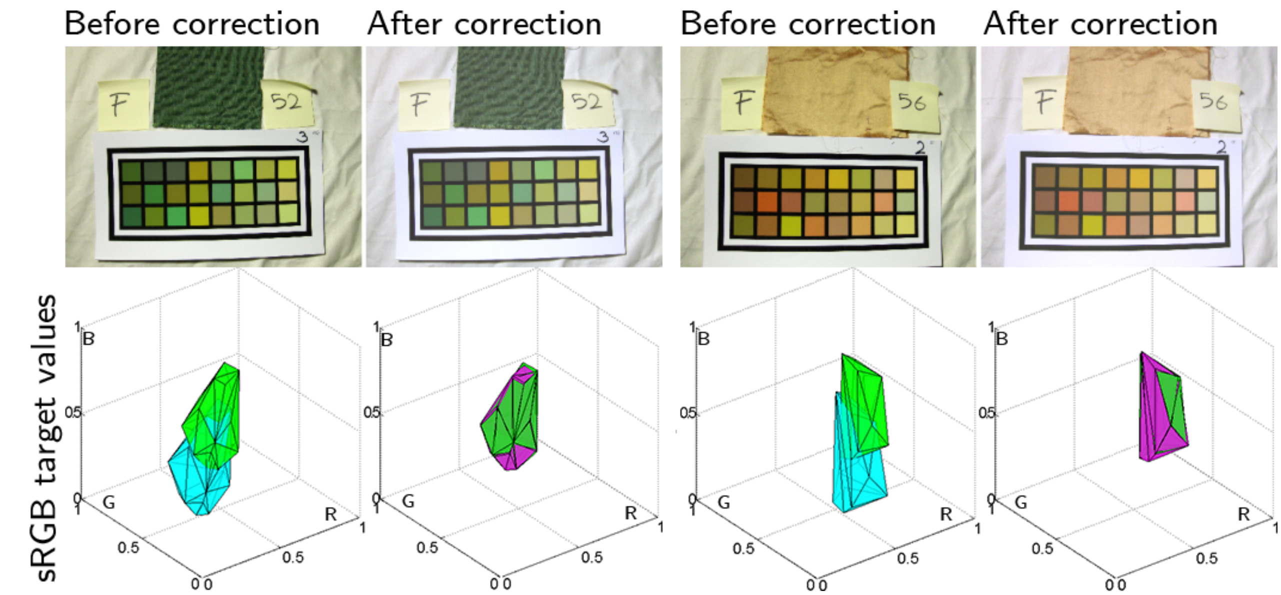

Figure 2. *Examples of before/after color correction of 2 objects. All the samples were imaged in the same conditions, but automated in-camera processing shows important variations. Under each pair of images, we show the convex hulls of the image uncorrected target values (cyan), reference target values (green), and image corrected target values (magenta). The reference values are calculated from the reflectance spectra of the target, converted to sRGB. The corrected values and reference values overlap.*

era responses, especially when $n \ll 31$. For many applications, however, it is sufficient to retrieve colorimetric values instead of the entire reflectance spectra. The human visual system is indeed unable to recover spectral information and two objects having the same appearance under a given illuminant can have slightly different reflectance spectra $S(\lambda)$. A three channel camera is then sufficient to retrieve tristimulus values. Several approaches using RGB cameras as colorimeters have been proposed. Wu et al. [13] use a calibrated camera to compute transforms from camera RGB to CIEXYZ by either minimizing a cost function in CIELAB space or by minimizing the mean square error in CIEXYZ color space under several selected illuminant conditions. The application was the colorimetry of human teeth. Hubel et al. [6] present a method to compute 3×3 color transform matrices intended for camera calibration in digital photography by simple least squares regression, white point preserving least squares regression, and weighted white point preserving least squares regression. This type of approach allows using a calibrated camera as a colorimeter under known illuminant conditions.

Such calibration methods require the access to the raw data of the sensors and the resulting color transform is camera dependent. The transform is usually applied prior to the image rendering implemented in the camera. In our method, we apply the transform *after* color rendering. As such, we need no information about sensor characteristics and in-camera processing, but we need to calculate a transform for every single image. Our transforms are scene and camera dependent.

Our approach

We propose a method to retrieve color information from digital images taken with a single, casually posed consumer camera under unknown illuminants. The method is targeted towards consumer applications, such as Home Décor advice. The users are assumed to use an unknown camera in fully automatic mode and under uncontrolled lighting conditions. We suppose that the camera performs white-balancing and encodes images in sRGB, which has a defined illuminant of D65.

Due to imperfect illuminant compensation, different sensor responses, and variations in image processing and quality across devices, uniform color rendering is never achieved. The resulting image color values of a given scene captured with different uncalibrated cameras or under different lights can have significant variations.

To classify colors consistently, we need the same object to have similar sRGB pixel values independently of the illuminant and the camera. We have no access to the raw data of the sensors and no additional information on the automatic in-camera processing. We thus compute a color transform using known reference values present in the scene in the form of a calibration target. Note that the reference colors need to be “close” to the actual color to be corrected, as it is not possible to correctly map all colors with a simple linear transform. Only a limited range of colors can be accurately corrected with a given transform.

Previous work was targeted towards skin color assessment [5]. Using a color target consisting of patches covering the range of possible skin tones, we demonstrated that we could assess skin color with an accuracy under $\Delta E^*_{ab} = 1$ [8]. The gamut of skin tones being limited, we could color correct any image using a single target. Skin tones span a hue angle of about 20° in CIELAB (see Figure 3). Considering that we could color correct skin tones with only one target, we can roughly estimate that $360^\circ/20^\circ = 18$ targets would be necessary to correct all hues with a similar accuracy. However, it is not practical for users to choose among so many targets. We thus decided to use nine targets covering all hues, at some cost in accuracy. We assume that high accuracy in color correction is more critical for skin tones than for the present application.

The system returns a set of paint colors coordinated with the color of the imaged object. The paint database consists of palettes of four colors (see Figure 4). We do not need exact color match-

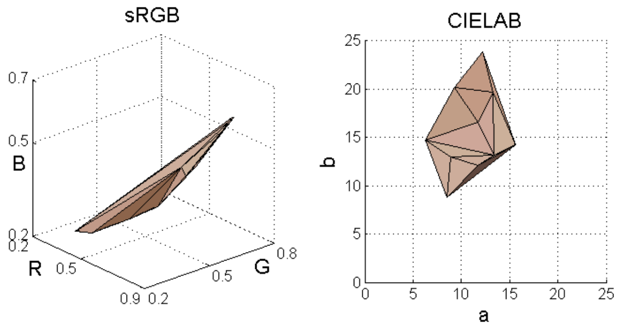

Figure 3. *Skin tones only represent a limited color range and span a hue angle of about* 20° *in CIELAB. The surfaces represent the color values of the target used for skin color correction covering the range of human skin tones in sRGB and CIELAB.*

ing. Rather, we are interested in selecting the closest matching shade in a color palette. The palette is the basis of our color coordination recommendation. Our metric of success is if the expert would have selected the same matching paint and palette of coordinating colors from the available set. That is, the advice can give solid guidelines to users in practical conditions such as what colors to add to a room while keeping an existing design element. The system has to work with a relatively low number of calibration targets and under many real conditions, such as limited palettes and non-uniformity of the samples.

Reference targets

The system uses a total of nine color correction targets. Eight targets consist of a selection of Munsell Colors covering a hue angle of roughly 60°. A target contains 24 patches. 21 come from 7 secondary hues distributed to cover a good range of chroma and lightness and three are paints extracted from our database. The range of colors of two adjacent targets overlap. Targets were ordered by similar hues to facilitate their use. Hue is the most natural attribute of color, it makes the choice of the target by visual matching much simpler for the users. Also, overlapping hues avoid having an object whose color may be in-between charts. We added a ninth chart made of 24 paint samples from the paint database covering a variety of beiges and browns, colors that are common in Home Décor and require a finer sampling. Figures 1, 2, and 4 show some target examples.

We printed the targets on matte paper, such that they are lambertian, and measured the reflectance spectrum of each patch. These measures allow computing first CIEXYZ values under illuminant D65 and then sRGB values. With reference to equation (1), $\mathbf{s}(\lambda)$ are the target reflectances, $\mathbf{e}(\lambda)$ is the standard CIE illuminant D65, and $\mathbf{r}_i(\lambda)$ are the 1931 CIE $\bar{x},\bar{y},\bar{z}$ color matching functions. The CIEXYZ to sRGB transform is specified in [1].

Color Transform

Users choose a chart according to the general color of the object and then image the object and chart together. The target patches are extracted, the color pixel values of each patch are averaged, and their mean values are compared to reference target values (sRGB triplets). A 3×4 color transform $\mathbf{A}$ maps the target patches mean color values $\mathbf{M}$ extracted from the image onto reference target values $\mathbf{T}$.

$$\mathbf{T}_{\{3\times n\}} = \mathbf{A}_{\{3\times 4\}} \cdot \mathbf{M}_{\{4\times n\}}\,, \tag{2}$$

where $\mathbf{T}$ is a matrix whose ith column contains the ith value of the n reference patches $\mathbf{t}_i = (t_i^{red}, t_i^{green}, t_i^{blue})^T$ and $\mathbf{M}$ is a matrix whose ith column contains the ith value of the n mean camera patch color $\mathbf{m}_i = (m_i^{red}, m_i^{green}, m_i^{blue}, 1)^T$.

We want to find $\mathbf{A}$ minimizing $\|\mathbf{T}-\mathbf{AM}\|_2$, i.e. minimizing the least mean square error in sRGB color space. $\mathbf{A}$ is computed using the Moore-Penrose pseudo-inverse denoted $^+$. Right-multiplying equation (2) by $\mathbf{M}^+ = \mathbf{M}^T(\mathbf{MM}^T)^{-1}$ gives $\mathbf{TM}^+ = \mathbf{AMM}^+ = \mathbf{A}$. Finally we obtain

$$\mathbf{A} = \mathbf{TM}^+\,. \tag{3}$$

The pseudo-inverse of $\mathbf{M}$ is computed by singular value decomposition. $\mathbf{A}$ provides a 3×3 color transform plus a per-component offset. Image extracted sRGB values are not rounded prior to the least mean square computation to increase the precision for dark objects, i.e. small sRGB values. $\mathbf{A}$ is recomputed for each new image and new target and will thus differ depending on the camera characteristics, lighting conditions, and the range of colors considered. It is applied to the entire image prior to the object's pixels extraction.

The spacing between the reference target colors is perceptually uniform. To approximately preserve this perceptual uniformity in the color correction, the linear transform $\mathbf{A}$ is computed in non-linear sRGB. Minimizing the least mean square error in sRGB is computationally fast and simple [5], but only ensures an accurate correction for colors that fall within the range of the calibration target colors. The target thus has to be carefully chosen for each new object and the overall color appearance of the corrected image outside that object may be poor.

Matching metric

After color correction, the object's pixels are assumed to be in sRGB. The object pixel values are converted from sRGB to CIEXYZ and then to CIECAM02. The object and paint samples are matched by minimizing their color difference in CIECAM02. Input data for CIECAM02 includes the tristimulus values XYZ of the object and of the white point $X_wY_wZ_w$, the adapting luminance L_A, and the relative luminance of the surround. Viewing condition parameters were chosen as advised for the previous model CIECAM97s when considering sRGB [9].

The Euclidian distance between the object's and paint's CIECAM02 values

$$\Delta E_{02} = \sqrt{(J_o - J_p)^2 + 100(a_o - a_p)^2 + 100(b_o - b_p)^2}\,, \tag{4}$$

where 'o' stands for 'object' and 'p' for 'paint', is minimized. J represents the CIECAM02 lightness and a and b are the *red - green* and *yellow - blue* components, respectively. These components were chosen by simplicity over the hue h and chroma C. a and b are multiplied by a factor 100 to adjust to the range of lightness J. Preliminary experiments returned better results when using a perceptually uniform color space over a simple Euclidian distance in sRGB. Moreover, CIECAM02 was chosen over CIELAB for its better overall perceptual uniformity. CIELAB indeed shows non uniformity in blue hues [10].

The algorithm

The algorithm consists of the following steps:

1. Users choose a target whose hue is similar to the hue of the object. They image the object and target together.
2. The target patches are extracted. The color correction trans-

Figure 4. Paint samples are grouped in palettes of four colors. The system matches the object color to one of the paints and returns the corresponding palette. The figure shows, from left to right, the uncorrected image, the corrected image, and the corresponding paint palette.

form (Equation 3) mapping the image target values onto reference values is computed and applied to the entire image.

3. The object's pixel values are extracted, averaged, and converted to CIECAM02.
4. The object color is compared against a collection of 63 coordinated paint palettes, each consisting of four colors, i.e. a total of 252 paints. The system chooses the paint best matching the color of the object in CIECAM02 (Equation 4).
5. The system finds the palette containing the best match and the three paints complementing its color, hence complementing the object (see Figure 4).

Experiment

Colored objects were imaged with an HP R-967 camera under uniform fluorescent light along with a properly chosen color calibration target. Fluorescent lighting conditions are common in office environments and stores, as well as in homes with the increasing use of energy-saving light bulbs.

The object database consists of 63 samples of various colors and materials. The samples were chosen such that their colors cover most hues. The choice of beige, brown, and wood-like samples is larger (26 samples) as these colors are very common in Home Décor. The samples are of wood (7 samples), linoleum (8 samples), including some mimicking wood, tiles (10 samples), including two semi-transparent glass tiles, kitchen top samples (6 samples), and fabrics (32 samples). We intentionally chose different, textured, non uniformly colored, and non lambertian samples to test the system in "real" conditions. However, the database only contains flat and relatively smooth samples, our method may thus have to be adapted depending on the geometry of the considered decoration object. The database and the targets were created independently, i.e we did not use the targets as references while collecting samples.

The object CIECAM02 values are compared against the CIECAM02 values of 252 paint samples by minimizing the Euclidian distance (4). The system picks the paint closest to the object. Paint samples are grouped in palettes of four colors. The system thus returns four colors, one matching and three complementing the object color.

Home Décor expert rating of the results

A Home Décor expert was shown each sample along with 9 color palettes, i.e. a total of 36 paints. The expert was first asked to choose the paint out of 36 that she would pick as best match. The database of paints did not offer enough colors for her to systematically pick an optimal color. The expert was thus asked to rate her own choices. The grades go from 1 to 5 according to the following rating:

1. The sophistication of a high quality expert recommendation, perfect given the palette selections
2. Competent work by an expert given the palette selections
3. Close, but not perfect, typical of an untrained consumer
4. Poor selection, other selections are much better
5. Terrible, unacceptable, even for a consumer.

The expert was asked to give integer grades and keep uniform intervals between grades. After she made her choice, we presented her the system's results and asked her to rate them as previously. The system's and expert's results were then compared and analyzed.

The expert gave the grade 1, meaning "perfect", to 29 of the 63 paints selected by our system, while she similarly rated 47 of her own choices. The grades occurrences can be seen in Figure 5. The system and expert top choices match for one third of the objects, but the remaining results are also good. Many different paint patches have very similar CIECAM02 values, especially in beige tones. The expert graded most of the system results 1 - as right on - or 2 - good for an expert. The average grades are 2.09 ($\sigma = 1.34$) and 1.57 ($\sigma = 1.21$) for the system and expert, respectively. These results are satisfying, but do not take into account the quality of the color correction.

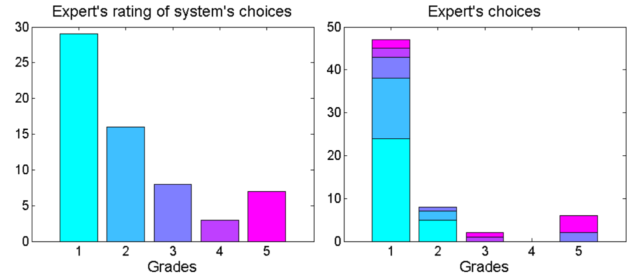

Figure 5. This figure shows the occurrence of each rating, for the system (left) and expert (right) choices. The colors in the right plot correspond to the grades of the system's choices.

Color correction accuracy

The color correction matrix **A** maps the target patch values extracted from an image onto reference values. We can visualize this color correction by looking at the convex hulls of the reference, image extracted, and color corrected target values in normalized sRGB. Figure 2 shows two examples of color correction and the corresponding target values in sRGB.

Due to the variety of non lambertian and textured materials in the set, the quality of the color correction cannot be estimated using sample reflectance spectra. However, it can be estimated using the target patches, which are known, and a leave-one-out method. Each target patch is successively corrected using a color correction transform computed from the 23 remaining patches. The error in color correction is computed as the difference between the patch image extracted normalized sRGB values after color correction and the corresponding reference values. This is done for the 24 patches extracted from the 63 images, i.e. for a total of 1512 patches. The average error in normalized sRGB target values is 2.02% ($\sigma = 1.02\%$). The equivalent error in CIECAM02

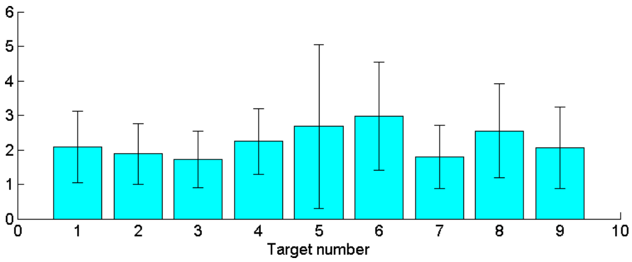

Figure 6. *ΔE_{02} (Eq. 4) error amplitude in color correction for each of the 9 targets. The results are obtained using a leave-one-out approach on the target patches. The bars show the standard deviation σ.*

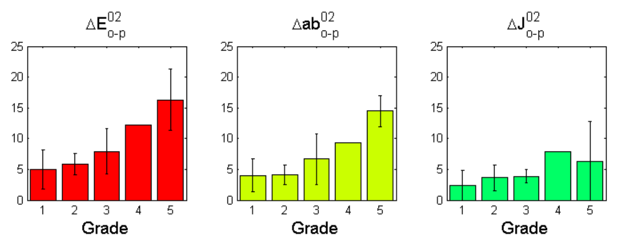

Figure 7. *ΔE_{02} differences between the object and paints colors as a function of the grades given by the expert computed for the 38 samples satisfying Equation (5). Δab stands for $\sqrt{\Delta a^2 + \Delta b^2}$. The bars show the standard deviation σ. Only one sample was graded as 4.*

is $\Delta E_{02} = 2.19$ $(\sigma = 1.17)$. Figure 6 shows the color correction ΔE_{02} errors for each of the 9 targets. The error is target dependent.

The color correction of an object is good if its color is similar to the colors in the calibration target. In other words, the color correction accuracy depends on whether the object color is located "close enough" to the volume formed by the target values in sRGB. The targets gamuts do not fill the entire sRGB cube, i.e. the targets are not optimal for all the samples. We tested which samples are accurately color corrected by looking at the position of the object color in sRGB with respect to the convex hull of the corresponding calibration target. We used as criterion the difference in volume between the convex hulls of the target points with the object color point V_{t+o} and of the target points alone V_t. The color correction is classified as sufficient if the difference in volume is less than 10%, i.e if

$$\frac{V_{t+o} - V_t}{V_t} < 0.1\,. \tag{5}$$

38 samples satisfy the criterion. The distribution of grades among these 38 samples is as follows: 18 samples receive a 1, 12 samples a 2, 3 samples a 3, 1 sample a 4, and 4 samples a 5. The remaining 25 samples will be ignored for a more precise analysis in the following results. Figure 5 takes all 63 samples into account, while Figures 7 to 9 use the 38 samples satisfying (5).

Note that this procedure can be used to provide feedback to users and help them dynamically choose the calibration target. Future versions of the system will be able to test whether the object color falls within the target gamut and indicate whether the object can be adequately color corrected. If it is not the case, the system will indicate which target the users should employ.

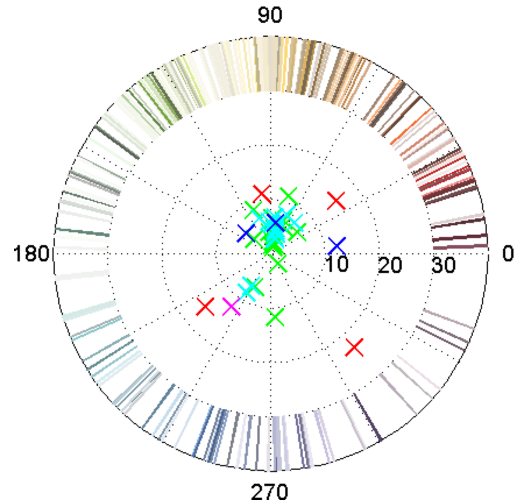

Figure 8. *The distance between the crosses and the origin corresponds to the CIECAM02 differences ΔE_{02} between the paints and objects computed for the 38 samples satisfying Equation (5). The angles represent the objects hues. The color of the crosses corresponds to the grades - 1 is green (18 samples), 2 is cyan (12 samples), 3 is blue (3 samples), 4 is magenta (1 sample), and 5 is red (4 samples). The colored lines correspond to the paints in the database ordered by their hue angle.*

Expert rating correlates with ΔE_{02} differences

The goal of this experiment is to determine if we can give automated color advice that an expert would consider as good. The two critical factors are the quality of the color correction and the metric used to match the objects with the paint samples. We have seen that, when the target is correctly chosen according to the object's color, the color correction is "good" with an accuracy of 2.02% in sRGB.

We assume that we can mimic how an expert matches the sample and paint colors by minimizing the CIECAM02 distance between them. We verify the validity of this assumption by comparing the CIECAM02 distance (4) used by the system to assign matches with the grades the expert gave to the results. Figure 7 clearly shows that the paints that are close to the object in CIECAM02 ($\Delta E \sim 5$) get the best grade 1. Figure 7 also shows that the difference in (a,b) is more critical than the difference in lightness J, larger distances Δab correspond to poorer grades (middle plot), while the distance in lightness ΔJ does not exhibit any specific relation with the expert's grades (right plot). Figure 8 shows the same CIECAM02 differences as Figure 7, ΔE_{02} distances being represented on a polar plot. The radius, i.e. the distance between a cross and the origin, corresponds to the CIECAM02 difference between the object and the selected paint. The polar angle corresponds to the object hue. The colored lines correspond to the 252 paints in the database, also ordered by their hue angle. This alternative representation of the results shows how the objects and paints are distributed in hue. It also shows that bad grades 4 and 5 (magenta and red crosses) mostly correspond to object hue angles for which the paint density in the database is low.

A modified metric for better results

The above results suggest that hue plays a more important role to the expert than lightness when choosing color matches. The current metric (4) can be modified to give less weight to light-

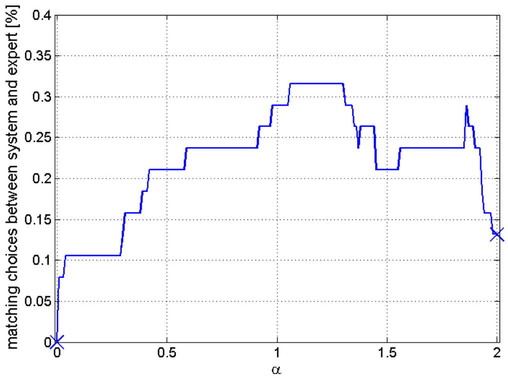

Figure 9. *The metric is optimized by weighting the lightness J with respect to (a_c, b_c) by varying α. The optimum is chosen as α such that the highest number of system and expert recommendations match.*

ness. Moreover, the CIECAM02 model defines cartesian coordinates that are better perceptual attributes than the approximated cartesian coordinates $100a$ an $100b$ used in (4). The Cartesian coordinates (a_c, b_c) for chroma are defined as [3]

$$a_c = C\cos(h) \qquad \textit{and} \qquad b_c = C\sin(h)\,, \tag{6}$$

where C is the chroma and h the hue angle. We tested a new metric by varying the parameter $\alpha \in [0,2]$ in

$$\Delta E_{02}^{c,\alpha} = \sqrt{(2-\alpha)(J_o - J_p)^2 + \alpha[(a_{c,o} - a_{c,p})^2 + (b_{c,o} - b_{c,p})^2]} \tag{7}$$

in order to better match the expert method of picking color matches. When $\alpha = 1$, Equation 7 simply becomes

$$\Delta E_{02}^{c} = \sqrt{(J_o - J_p)^2 + (a_{c,o} - a_{c,p})^2 + (b_{c,o} - b_{c,p})^2}\,. \tag{8}$$

We varied α by 0.01 steps and ran our system for each α. We computed how many newly assigned paints match with the expert choices for each iteration. Figure 9 shows the result of the optimization. We see that giving slightly more weight to the a_c and b_c components gives better results. The maximum is centered around $\alpha \sim 1.2$. Looking at the two extreme cases $\alpha = 0$ and $\alpha = 2$ also shows that hue is more important than lightness for the expert. Indeed, completely discarding the lightness $(\alpha = 2)$ still gives some matching results, while we do not obtain any match when $\alpha = 0$.

Conclusion

Accurate color cannot be retrieved from uncalibrated images taken with uncalibrated cameras. However, a limited range of colors can be estimated by using appropriate color information in the form of a target present in the scene. A color transform mapping the scene target color values onto pre-computed target reference values is computed by least mean square estimation in sRGB and applied to the entire image. The least mean square estimation of the color correction matrix in sRGB allows a fast and computationally low-cost color correction.

We demonstrate that this method can be successfully applied to Home Décor applications. Any color can be corrected using a limited number of color calibration targets. When the colored object is within the target colors' convex hull, its color is corrected with an accuracy of $\Delta E_{02} \cong 2.19$ ($\Delta E_{02}^{c} \cong 2.03$).

We show that we can assign coordinated colors to any colored object by minimizing a CIECAM02 distance between the object color and a database of paints. We obtain results similar to what an expert would achieve. The metric can be modified by giving more weight to hue to even better match the expert's selection.

The method assumes a uniform illuminant across the image, but shadows and mixed illuminants can be important sources of error. The variety of texture and reflective properties of objects in Home Décor can also lower the color correction accuracy.

We demonstrated the validity of our color correction method in the specific framework of Home Décor. However, the method can be easily generalized to other applications.

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