

# Photo-Realistic Color Alteration for Architecture and Design

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**ABSTRACT:** As color is a strong stimuli we receive from the exterior world, choosing the right color can prove crucial in creating the desired architecture and design. We propose a framework to apply a realistic color change on both objects and their illuminant lights for snapshots of architectural designs, in order to visualize and choose the right color before actually applying the change in the real world. The proposed framework is based on the laws of physics in order to accomplish realistic and physically plausible results.



Figure 1 Comparison: (a) Original Image; (b) Proposed Model; (c) Recoloring using proposed method (d) Recoloring using a state-of-the-art photo-editor

1 INTRODUCTION AND RELATED WORK : Color is an important aspect in the world of design and architecture. According to Leon V. Solon, color in its architectural relation must naturally be classified as a decorative resource. Each decorative resource has the capacity to realize a distinctive type of effect unattainable by the legitimate use of any other decorative means [10]. Many psychophysical studies have been performed on the effect of color in architecture and on human beings as color is a strong stimuli we receive from the exterior world [6]. Different colors can create different environments, and therefore a change in color can prove crucial in transforming the space into the desired design.

The urge for a realistic re-coloring method rises when an architect needs to obtain a particular object in another color or lighting condition (e.g, warm-tone sunset or cold-tone early morning) to create the desired effect. Depending on the design, it's not always possible to create all the possible options to choose from. Virtual reality and 3D-Modeling packages (Computer Aided Design) are often used to visualize and facilitate the design. While the quality of these models are not often satisfactory, in the case of re-decoration and renovations, a model of the whole space should be built in order to check different color combinations. Our aim here is to create a framework which is capable of illustrating the color changes without the need of CAD softwares and with photo-realistic quality.

Color modification and re-coloring embedded in professional photo-editing applications performs by calculating an offset in the hue, saturation and luminance between the source and destination colors. The source image is adjusted to produce the desired color [4]. Although such method is quite fast, it suffers from a lack of physical foundation to correctly separate object reflectance from illuminant color leading to a less realistic result, while requiring prior segmentation.

Here we propose a physics-based method to achieve a high quality re-colored image by extracting the physics-based geometrical model of the light interaction with the object surface. Yet we have managed to maintain a fairly low computational cost and, with the exception of object segmentation, virtually no user interaction is required. Furthermore, the proposed framework is capable of applying the color changes both on the object and its illuminant light using the same physics-based model. Section 2 and 3 are devoted to a brief description of the model and the method respectively. A more in depth explanation of the framework can be found in [2].

2 COLOR MODELING AND RECOLORING : In order to develop a better understanding of the light interaction with the object surface, we use a physics-based model of reflection called the *Dichromatic Reflection Model* [8]. Using this model we are able to generate a snapshot of

that object with the same imaging condition varying only the chromaticity of the object and illuminant light.

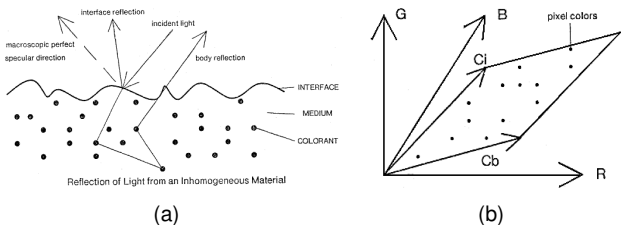


Figure 2 (a) Reflection of the light from an inhomogeneous material; (b) Pixel values for a set of points on a single surface lie within a parallelogram in color space. Images are taken from [8]

**2.1 Dichromatic Reflection Model (DRM) :** According to Shafer, pixel values for a set of points on a single surface must lie within a parallelogram in the RGB space, bounded by RGB vectors  $\mathbf{C}_i$  and  $\mathbf{C}_b$  (here on we indicate vectors in bold font). These vectors represent the direction of the interface and body reflectance from the object surface respectively (Figure 2(b)). The validity of the dichromatic model has been proven for a variety of inhomogeneous dielectric materials commonly observed in natural scenes [12]. Although this model does not assume a point light or uniform illumination distribution over the scene, it requires a prior segmentation (Figure 3(b)) for multi-colored objects in order to fulfill the assumptions of the model.

The dichromatic model can describe the color of each pixel inside a single-colored object and illuminated by a single-colored illuminant, using images of the amount of body ("diffuse") and interface ("specular") reflections at each pixel which are called *intrinsic* images (Figure 3(c) and 3(d)) and first introduced by Barrow and Tenenbaum [1]. The dichromatic model in the mathematical format is demonstrated below,

$$\mathbf{f} = m_b \mathbf{C}_b + m_i \mathbf{C}_i, \quad (1)$$

where  $\mathbf{f}$  is the RGB triple defining the color of every pixel in the object surface,  $m_b$  and  $m_i$  are the intrinsic images

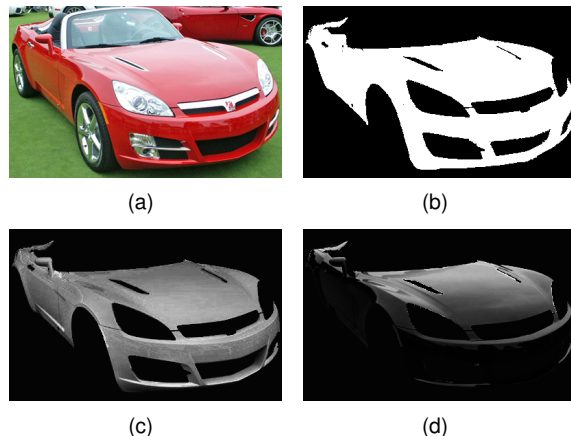


Figure 3 The DRM fitting: (a) The original image; (b) Segmentation mask; (c) and (d) are the intrinsic images for body and interface reflectances respectively.

of body and interface reflectance respectively, and  $\mathbf{C}_b$  and  $\mathbf{C}_i$  are the colors of the corresponding colors.

Several methods have been developed to approximate the dichromatic model of an object. Whether using a spatial-based approach in which the two dichromatic planes for specular and body reflectance are approximated considering the lighter and darker pixels separately [5], or with the assumption of a known illuminant [9, 11]. Later on in Section 3 we propose a novel method in which a fairly accurate approximation of the dichromatic plane of an object under an unknown illuminant is achieved.

**2.2 Intrinsic images estimation :** Using the correlated RGB color space the dichromatic equation can be solved with the assumption that the  $\mathbf{C}_b$  and  $\mathbf{C}_i$  color vectors are constant for the entire object to be re-colored (single-colored object and illuminant). The material coefficients ( $m_b$  and  $m_i$ ) are fixed for each pixel which means the coefficients are the same for R, G, and B values of the same pixel. Then for an image of  $N$  pixels, we would have  $3 \times N$  equations (Equation 2) while the number of unknown values would be  $2 \times N$  for  $m_b$  and  $m_i$  in addition to the 6 values defining the RGB triples

of  $\mathbf{C}_b$  and  $\mathbf{C}_i$  color vectors. Having said that, for a large enough number of pixels, this set of equations can then be solved in least-square sense. Algorithms for approximating  $\mathbf{C}_b$  and  $\mathbf{C}_i$  are proposed in section 3

$$\begin{pmatrix} R_j \\ G_j \\ B_j \end{pmatrix} = m_{b_j} \begin{pmatrix} C_b^R \\ C_b^G \\ C_b^B \end{pmatrix} + m_{i_j} \begin{pmatrix} C_i^R \\ C_i^G \\ C_i^B \end{pmatrix} \quad (2)$$

Therefore, given the RGB values of  $\mathbf{C}_b$  and  $\mathbf{C}_i$ , and using the pixel RGB values  $\mathbf{f}$ , we are able to calculate the intrinsic image matrices  $m_b$  and  $m_i$  which minimize the fitting error of the model to the object pixels (Equation 3). Note that the pseudo-inverse notation implies the least square error minimization.

$$\begin{bmatrix} m_b \\ m_i \end{bmatrix} = pinv \left( \begin{bmatrix} C_b^R & C_i^R \\ C_b^G & C_i^G \\ C_b^B & C_i^B \end{bmatrix} \right) \mathbf{f} \quad (3)$$

**2.3 Gamma Correction :** Using uncalibrated RGB color images one should bear in mind that due to the *Gamma expansion* that occurs largely in the nonlinearity of the electron-gun current-voltage curve in Cathode Ray Tube (CRT) monitor systems, image signals are *gamma encoded* prior to be shown on monitors [7]. Therefore a *Gamma Correction or decoding* process should be performed to preserve the linearity of the color signals prior to the DRM approximation. Here we have set  $\gamma$  to be 2.2 for sRGB color space.

**2.4 Color alteration or Recoloring :** The main goal of our method is changing both object and illuminant colors. After the estimation of the object reflectance model, recoloring of the object is straightforward. The entire color alteration process is demonstrated in the Equation 4, where  $\mathbf{f}'$  is the object reflectance in the new body and illuminant color ( $\mathbf{C}_b'$  and  $\mathbf{C}_i'$  respectively) specified by user.

$$\mathbf{f}' = m_b \alpha \mathbf{C}_b'' + m_i \mathbf{C}_i' \quad (4)$$

$$\mathbf{C}_b'' = \begin{bmatrix} C_i^{R'}/C_i^R & 0 & 0 \\ 0 & C_i^{G'}/C_i^G & 0 \\ 0 & 0 & C_i^{B'}/C_i^B \end{bmatrix} \mathbf{C}_b' \quad (5)$$

Note that according to the model (see Figure 2(a)), the body reflectance itself relies also on the illuminant color. Therefore, we have modeled the effect of illuminant color changes on the object surface using the term  $\mathbf{C}_b''$  which is defined as in Equation 5. Since color vectors are normalized, we introduced the term  $\alpha$  to simulate the desired change in the color intensity.

Despite the computational complexity of the dichromatic plane estimation, the re-coloring algorithm is simple addition and multiplication operations which, implemented in logic-gates, would perform in real-time.

**3 CHROMATICITY ESTIMATION METHODS :** In this section we propose two methods for the estimation of the body reflectance color  $\mathbf{C}_b$  and interface reflectance color  $\mathbf{C}_i$  (Figure 4(c)) respectively. The body reflectance color ( $\mathbf{C}_b$ ) is estimated using Singular Value Decomposition (SVD) regardless of illuminant color. And the Planckian Locus concept is used to form the illuminant color ( $\mathbf{C}_i$ ) estimation method.

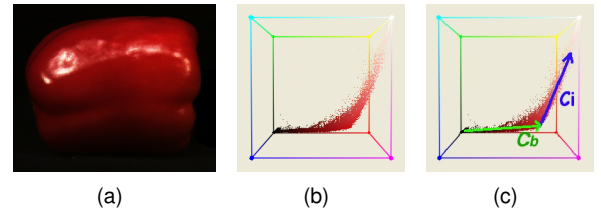


Figure 4 A single-colored object: (a) Original image; (b) RGB color histogram; (c) Expected directions for  $\mathbf{C}_b$  and  $\mathbf{C}_i$  vectors;

**3.1 Body reflectance color estimation :** The object pixel values for which the  $m_i = 0$ , form a line passing through the origin. Fitting a line through these pixels allows us to compute  $\mathbf{C}_b$ . The fitting error of an object pixel to a line given by the vector  $\hat{\mathbf{v}}$  is

$$e(\mathbf{x}) = \left\| \mathbf{f}(\mathbf{x}) - \left( (\mathbf{f}(\mathbf{x}))^T \hat{\mathbf{v}} \right) \hat{\mathbf{v}} \right\|. \quad (6)$$

The above Least Squares error minimization problem can be solved using SVD, where the eigenvector which corresponds to the higher eigenvalue is desired. Intuitively, having the assumption that most of the object pixels belong to the body reflectance, the higher eigenvalue is expected to indicate the  $\mathbf{C}_b$  direction.

**3.2 Illuminant chromaticity estimation :** The chromaticity of common light sources is limited and follows closely the Planckian locus of black-body radiators which is believed to be a function of temperature  $T$  in Kelvins [3]. For this matter we sample the colors of the Planckian Locus (Figure 5) for the standard illuminants ( $T \in 4000 \sim 25000$  with steps of  $1000 K^\circ$ ). Then the dichromatic equation is solved for all the pixels of the colored object using each of the possible illuminants, and  $m_b$  and  $m_i$  values are calculated. The illuminant chromaticity ( $\mathbf{C}_i$ ) which minimizes the object reconstruction error (Equation 7) would be chosen, and the corresponding  $m_i$  and  $m_b$  values for each pixel are then considered as the dichromatic model of the object.

$$E(\mathbf{C}_b, \mathbf{C}_i) = \sum_j \frac{((\mathbf{f}_j - m_b \mathbf{C}_b - m_i \mathbf{C}_i)^T \times (\mathbf{f}_j - m_b \mathbf{C}_b - m_i \mathbf{C}_i))}{(\mathbf{f}_j - m_b \mathbf{C}_b - m_i \mathbf{C}_i)} \quad (7)$$

**4 RESULTS :** A set of natural images have been recolored using our framework. Figure 6 illustrate the recoloring results obtained with the proposed framework. Realistic results achieved suggest that the proposed framework outperforms previous work on recoloring in which the underlying physics rules have been disregarded.

Note that few existing methods which make use of physics-based reflectance model, have only presented the results on a set of images under laboratory restricted conditions [9]. To best of our knowledge, these

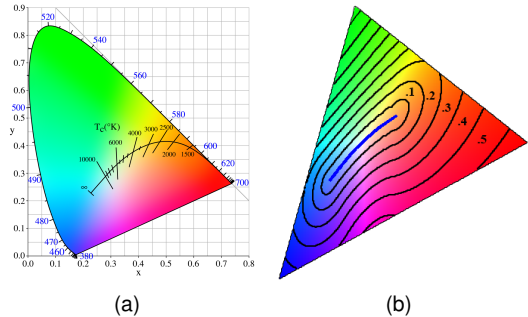


Figure 5 The chromaticity of common light sources: (a) The Planckian Locus inside the color gamut for CIE XYZ color space; (b) Color regions for which the distance to the Planckian Locus are in the same range.

are the first reported results for reflectance estimation in real-world images with complex shading and highlights.

**5 CONCLUSION AND FUTURE WORK :** We have presented a photo-realistic color alteration method for the pre-segmented images, in order to facilitate the color selection in architecture and design. The proposed framework is capable of applying the color changes both on the object and its illuminant light using the same physics-based model. The experimental results on natural images taken with non-calibrated cameras indicate that realistic recoloring of an object with highlights, shadows, and complex shapes is achieved.

We propose, as our future work, to embed into the framework a segmentation method, and to make use of psychophysical experiments to introduce a quantitative error measurement.

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References





Figure 6 Recoloring a set of natural images. The first row: An example of an outdoor scene (city of Bryggen, Norway) The second row: An example of an interior scene.

- [1] H.G. Barrow and J.M. Tenenbaum. Recovering intrinsic scene characteristics from images. In *A. Hanson and E. Riseman, editors, Computer Vision Systems*, 1978.
- [2] Shida Beigpour. Master thesis: Physics-based reflectance estimation applied to recoloring. *Computer Vision Center, Universitat Autònoma de Barcelona*, July 2009.
- [3] G.D. Finlayson and G. Schaefer. Solving for colour constancy using a constrained dichromatic reflection model. *International Journal of Computer Vision*, 42:127–144, 2002.
- [4] R. Gonsalves. Method and apparatus for color manipulation. *United State Patent 6,351,557*, Feb 26, 2002.
- [5] V. Kravtchenko and J.J. Little. Efficient color object segmentation using the dichromatic reflection model. *Communications, Computers and Signal Processing, 1999 IEEE Pacific Rim Conference on*, pages 90 – 94, 1999.
- [6] Frank H. Mahnke. *Color, Environment, and Human Response: An Interdisciplinary Understanding of Color and Its Use as a Beneficial Element in the Design of the Architectural Environment*. 1996.
- [7] Ch. Poynton. *Digital Video and HDTV Algorithms and Interfaces*. 2003.
- [8] A. Shafer and D. Lischinski. Using color to separate reflection components. *Color Research and Application*, 10(4):210–218, 1985.
- [9] H.L. Shen and J.H. Xin. Transferring color between three-dimensional objects. *Applied Optics*, 44(10):1969–1976, 2005.
- [10] Leon V. Solon. Principles of architectural polychromy, part i: The conditions which control the introduction of color. *The Architectural Record*, January 1922.
- [11] R.T. Tan and K. Ikeuchi. Separating reflection components of textured surfaces using a single image. *Computer Vision, IEEE International Conference on*, 2:870, 2003.
- [12] S. Tominaga and B.A. Wandell. Standard surface-reflectance model and illuminant estimation. *Journal of Optical Society of America*, 6(4):576–584, 1989.