Example-based Image Recoloring in Indoor Environment

Xianxuan Lin

Xun Wang

Frederick W.B. Li

Jinyu Li

Bailin Yang*

Kaili Zhang

Tianxiang Wei

Abstract

Color structure of a home scene image closely relates to the material properties of its local regions. Existing color migration methods typically fail to fully infer the correlation between the coloring of local home scene regions, leading to a local blur problem. In this paper, we propose a color migration framework for home scene images. It picks the coloring from an template image and transforms such coloring to a home scene image through a simple interaction. Our framework comprises three main parts. First, we carry out an interactive segmentation to divide an image into local regions and extract their corresponding colors. Second, we generate a matching color table by sampling the template image according to the color structure of the original home scene image. Finally, we transform colors from the matching color table to the target home scene image with boundary transition maintained. Experimental results show that our method can effectively transforms the coloring of a scene matching with the color composition of a given natural or interior scenery.

Keywords: home scene image, coloring expectation, color structure, color migration, interactive operation

Introduction

Coloring is a predominant factor influencing object attractiveness perceived by human [1]. Different color combinations impose distinct effects to each person, implicitly defining object or scene styles. In a home scene, furniture location is an extra factor on top of coloring to determine how a person perceives the home scene design.Following this, interior decorators can effectively convey ideas of good designs and pleasing color combinations to their customers by presenting images of different home scene coloring designs. A design comprises style and color, determining how well a set of collocated furniture goes well with each other aesthetically.

Home scene coloring research follows two major directions: 3D model based and image based color migration. 3D model based methods explore color scheme according to the coloring of individual home scene objects, which is usually well defined as each object is an independent entity from each other. However, a 3D scene is often expensive to obtain in terms of time and modeling effort. In contrast, in image based color migration methods, coloring of home scene objects is challenging to obtain, since local image regions and their boundaries are not natively defined. This is usually addressed by applying certain mechanism to extract meaningful regions (or objects). For implementation, existing methods often perform global color migration without considering spatially local color properties and interactions, leading to undesirable local color distortion. To allow flexible and promising coloring design migration, we should also study color structure, which is modeled by the relationship between coloring and furniture parts in a home scene, and involve color structure transformation in a color migration process. Nevertheless, such a relationship is not trivial to establish.

Home scene image color migration is a challenging research. We have to solve a number of problems, including scene segmentation, scene part relationship modeling, and user expectation interpretation. To address the problems, we have developed a novel framework for migrating colors from a template image of natural or interior scenery. Judging from intuitiveness and simplicity, our work is favorable to both professional interior decorators and non-professional users. Main contributions of our work include:

- **Template coloring transformation:** We allow faithful transformation of user expectation through maximizing color variety, aligning color proportion and maintaining color relationship.

- **Regional color structure extraction:** We incorporate interactive segmentation to identify proper color regions and construct hierarchical color structure.

- **Multi-subgraph based color reconstruction:** We perform efficient color reconstruction by color cluster migration and hole repairing.

For the rest of the paper, section 2 presents related work. Section 3 gives a framework overview, and Section 4 depicts the basis of home scene coloring. Section 5 elaborates the color migration method. Section 6 and 7 presents experiment results and concludes the paper, respectively.

Related Work

Home scene color processing spans multiple directions, including color organization processing, dominant colors extraction, color table strategy, and color transfer. Existing work usually simply process a home scene according to certain color schemes, rather than exploiting the color spatial relationships.

Color Organization Processing

Investigating color organization of indoor home scenes is an important research topic in computer graphics and vision. Common approaches are 3D model based [2–5] or image based [6–8]. 3D model based methods rely on pre-defined home scene object (or furniture) definitions, which are not natively available in images. Hence, it is not feasible to simply adopt model based methods to image based ones. In existing work, Wang et al. [6] proposed an emotion-based image colorization system, requiring users to interactively segment the grayscale image of an indoor scene and associate the scene with a set of labeled furniture images, which are externally collected. This work is hard to generalize for color migration. [7,8] performed global image color transformation based on certain color space constraints, e.g., hue histogram normalization and scene illumination. In contrast, transforming colors by considering the relationship among furniture regions and their coloring in a home scene image can be categorized as local color transformation, which is a challenging problem.

Dominant Colors Extraction

Overall perceived hue of an image can be well represented by some dominating hues. Examining dominant colors is popularly done by color clustering [9–11]. However, it fails to maintain relative coloring of local image regions, matching with their physical characteristics. Alternatively, machine learning can be used to extract primary color, modeling how people perceive image color themes. Lin et al. [12] used a regression model to train a model for characterizing human-extracted themes and performed image theme extraction. This method processed coloring globally, failing to account for color relationships among scene part items.

Color Table Strategy

Several online communities devoted to share and create color themes, including Adobe Kuler [13] and COLOURloverss [14]. Most of their themes are extracted from images, comprising a small fixed number of colors, which are not quit suitable for directly transforming colors of home scene images, because such images generally possess more colors. Generating a color theme from an image may serve as a good reference for recognizing physical beauty of the image or restoring color relationships of the image. [15,16] have confirmed that different color combinations impose distinct feelings for individual human viewer. Color harmonic model [17] was then developed to evaluate whether a color pair is harmonic. This evaluation was only valid within a controlled environment, not being generalizable. [18] enhanced image color harmony by shifting hue values of image colors to fit a best harmonic scheme, while considering spatial coherence among colors of neighboring pixels. Alternatively, [19] proposed a data-driven model to evaluate the harmony of color combinations by scoring 5 colors from a color group. These methods only globally evaluated image coloring and depended on some fixed, small-sized color tables, being difficult to generalize for processing home scene images, which may comprise a much larger set of colors. Also, local region coloring of such images may possess physical significance due to furniture collocation, which cannot be properly handled by merely using a high-scoring, globally harmonic color table.

Color Transfer

Color transformation reconstructs target image coloring by some mapping rules. [20] proposed to adjust input image color statistics according to a template image under the lab color space, modifying the input image look and feel. Color transfer by [21] was performed by matching probabilistically segmented color regions and inter-region smoothness between the template and target images, where spatial correspondence among regions were optionally enforced. Some color transfer methods used nonlinear histogram matching [22–24] to handle global color migration. Alternatively, [11] used an improved k-means clustering to extract a color palette of a few representative colors from an image, allowing users to change some palette colors for modifying image coloring, while preserving luminance monotonicity and adjusting color change within the gamut boundary. All these methods mainly concerned color relationship within an image based on certain color statistics without observing their spatial correlation to scene objects. Local color distortion may then be resulted when they are adopted for home scene color transfer.

Overview

Our framework works based on modeling user expectation and properly identifying local scene regions:

User Expectation Modeling

To allow faithful transformation of user expectation into a home scene coloring design, we formulate three constraints to guide color migration, namely (1) maximizing the variety of template image colors for transferring to a target image, (2) aligning the proportions of different colors between template and target image, and (3) maintaining color relationship of a target image.

Local Scene Region Extraction

A critical success factor of image based home scene color migration is to identify semantic information of local scene regions. We should also account for user aesthetic preferences. To accommodate these, our framework involves user invention to form an additional guidance for color migration.

Workflow

Fig 2 illustrates the workflow of our framework with examples. It accepts a template image of user coloring expectation through natural (A) or indoor (B) scenery, transforming home scene image (target) coloring to produce image RA or RB, respectively. Our framework comprises regional dominant color extraction, matching color map generation, and multi-target collaborative migration. Specifically, regional dominant color extraction involves users to conduct home scene image segmentation, generating a color structure to formulate color-to-furniture relationship. Based on this color structure and a template image, we generate a matching color table with a simulated annealing algorithm, and perform color migration based on the table. Since we conduct color migration based on image segmentation, boundaries among image regions are prone to voids, we then introduce an operation to fix such boundary artifacts.

Basis of Home Scene Coloring

Color Features

Coloring Characteristics: We allows users to express their coloring design through images of natural scenery or indoor home scene. Interestingly, these images possess very different characteristics. Color transitions in natural scenery is typically gradual, while those in home scenes are generally discrete, as they are constituted of furniture, which likely possess some dominant coloring each. Typically examples of furniture are table and chair, which are usually movable, or window and door, which are usually fixed at an indoor location.

Scene Objects: Taking human perception into account, it is natural to divide a home scene into foreground and background objects. Foreground objects usually comprise furniture, which are placed in certain designated indoor environment positions. Their placement and coloring are typically local (with respect to an indoor environment), forming a critical relationship to represent user design preferences. In contrast, background objects usually refer to fixed house parts, such as wall and floor, with coloring widely spanning across a significant home scene portion.

Restricted Features: In a home scene, there are typically some features coming with unchangeable coloring, including outdoor scenery, indoor plants, collectables, etc. We should exclude them from color migration.

Hierarchical Color Structure

Many existing work only cast the color transformation migration problem as dominant colors discovery and replacement, solving them by color clustering algorithms and constraints. Scene object relationships and their relevance to scene coloring are usually ignored. In contrast, we use a hierarchical color structure to faithfully transform user expectation into home scene coloring design.

In our method, the color structure comprises three levels: (1) L1 globally categorizes a scene into foreground and background objects, (2) L2 maintains scene objects under each of the above category, allowing relationship among different furniture items to be represented, (3) L3 maintains the color components within each furniture item. Fig 3 illustrates the color structure of a home scene example. With L1, we maintain B and F, representing the number of colors in the background and foreground objects, respectively. BF represents restricted scene features. With L2, we maintain $B = (B_1, B_2, ..., B_n)$ and $F = (F_1, F_2, ..., F_n)$, representing the individual background and foreground object items, respectively. The color composition of these items is maintained under L3, e.g. $F_i = (c_1, c_2, ..., c_n)$ denotes the color set $(c_1, c_2, ..., c_n)$ formulating item F_i.

Color Map

Color map comprises a finite number of colors representing image content. Existing work store their color clustering results as a color map. Replacing some colors in a color map can change image tone or style. This operation generally cannot accommodate color change to regional image contents, due to lacking scene structure correspondence. To maintain color relationship, we argument color map with a two-level color relationship as described in Eq 1. For a color map $M = (c_1, c_2, ..., c_n)$, we average all color items $\overline{M}$ to produce a mean color m, forming the color map representative. As shown in Fig 4 (a), the first level color relationship is modeled by the distances between m and each color map element c_i, representing how image coloring spreads out from the representative. The second level color relationship is formed by the distances between each pair of color map elements, defining spatial relationship among all color elements. We evaluate color distance by using euclidean distance under the standard CIELab color space.

$$\begin{cases} \overline{M} \rightarrow c_i \quad i,j \in n \; and \; i \neq j \\ c_i \rightarrow c_j \quad i,j \in n \; and \; i \neq j \end{cases} \tag{1}$$

Color Migration Approach

After depicting how we model home scene coloring, we now present the two main components of color migration, namely regional dominant color extraction and matching color map generation. We also elaborate how the home scene coloring model can be incorporated.

Regional Dominant Color Extraction

User Assisted Segmentation: We exploit scene furniture and their color relationship to faithfully transform user expectation into home scene coloring design. Despite native color clustering may extract such information, noisy result is likely obtained for an input image, due to color or illumination variation appearing on individual furniture item. An example is shown in the middle and left parts of Fig 6, respectively. To properly extract dominant furniture coloring, we incorporate user intervention to assist color segmentation. We adopt an interactive segmentation algorithm [25] to divide a furniture item into parts by color and edge thresholds, which were implicitly defined by regions-of-interest indicated through user drawing strokes. As shown in Fig 5, a user can draw simple strokes over a furniture item to indicate foreground and background objects. For example, by drawing red and white strokes over a sofa as shown in the top-left part of Fig 5, foreground and background objects are then extracted respectively, as shown in the bottom-left part of the figure. Other parts of Fig 5 show other results based on different strokes applied. User assisted segmentation is intuitive since complicated scene or furniture item partitioning can be simply done by using multiple stroke drawing.

Color Extraction: After segmentation, a hierarchical color structure can be generated. For each furniture item, a subgraph is generated to represent color parts constituting a furniture item. This corresponds to L2 and L3 of the hierarchical color structure, where L3 color nodes can be directly obtained from the segmentation parts. Finally, L1 can be naturally formed by the foreground and background object categorization. To allow each furniture item to be processed as an independent entity during color migration, we derive a dominant color for each furniture item. This matches well with practical sense as each furniture item usually comes with a theme coloring defining its tone or style. We perform k-means clustering to determine the dominant color for each subgraph extracted, and utilize the resulting dominant colors to generate the home scene color map $C = (c_1, c_2, ..., c_k)$, where c_i is the ith color clustering center and k is the total number of clustering centers. An example of our color extraction result is shown in the right part of Fig 6. Our method explicitly works out the correlation between home scene structure and colors. In contrast, if only simple color clustering is applied for color replacement, confusing results may be produced as shown in the middle part of Fig 6. For instance, by replacing the white color of the sofa seats at the right side in the home scene, part of the ceiling color (white) will also be replaced unexpectedly.

Matching Color Map Generation

According to the input home scene color map produced, we determine a set of colors from the template image, using them to generate a matching color map. We cast this process as a combinatorial optimization problem constraining by both user interaction and visual color difference.

We uniquely allow users to express coloring expectation with a template natural or indoor scenery. If the template image is a home scene, color migration is quite straightforward as both template and target images comprise similar color structures. Such a benefit may no longer stand when natural scenery is used, as significant image parts may possess gradual color changes while scene objects could be ill-defined due to flexible shapes and motions, e.g. cloud and tree leaves. To overcome this, we migrate color separately for foreground and background objects.

Interactive color selection

Intuitively, a most simple approach to migrate color is to replace input home scene color map with the color map generated from a template image, while some optimization constraints can imposed to govern the quality of the results. As meeting user expectation is our key emphasis, we incorporate user interaction as part of the constraint to guide color migration. Particularly, a user can select a region of the target home scene for color migration, and select a region in the template image to indicate the coloring to be migrated. This will allow the corresponding color element in the color map of the target image to be replaced with the representative color picked out from the template image.

Optimization strategy

For foreground scene portion of color migration, colors of foreground objects can usually accept a wider change in intensity values. We obtain a color map from the template image. By simulated annealing, we align the color maps of template and target images by minimizing the distances between their corresponding elements. We add a luminance map to avoid unnecessary iterations, as the initial configuration of a simulated annealing process is typically generated randomly, making the process inefficient.

Matching Color Map: Given a template image, we apply clustering to generate a template color map $C = (c_1, c_2, ..., c_n)$, where n is the number of colors representing foreground objects. An example of color map (T) is shown in Fig 8. We further perform a detailed clustering on top to generate an extended color map $ET = c_{ij}, i = 1...a, j = 1...n$, comprising more fine-grained color elements, where c_{ij} represents the color of block i and point j in the image. An example based on color map T is shown in Fig 4 (c) (histogram at upper part), which also shows the color distribution. This offers users a finer control on the kind of results to produce. In practice, when we pick colors for migration using this extended color map, we should avoid choosing more than one color element from each block.

Luminance Map: Brightness relationship among colors of each image region is critical to color migration. It helps us single out color redundancy and improve color migration quality. We generate luminance maps to track the brightness information of the color maps. Fig 4 (b) shows the luminance maps ML and TL, generated for M (target color map) and T (template color map), respectively.

Simulated Annealing: We account for color contribution and structure for matching to support meaningful color migration. Color contribution corresponds to the percentage of pixels within an image space of a certain color. We measure color contribution separately for foreground and background image portions. For a target image and a template image, their color contribution maps are $R_M = (r_1, r_2, r_3..., c_n)$ and $R_T = (t_1, t_2, t_3..., t_n)$, respectively, where n is the number of color elements in their corresponding color maps. Measuring how well two color maps matched w.r.t. color contributions is evaluated by:

$$E_p = \sum_{1}^{n} |r_i - t_i| \tag{2}$$

Color structure is formulated by the two-level color relationship as described in Section

4.3, and mathematically defined by Rule 1. We may express the rule in an abstracted form as $V = (\alpha, \beta)$, where α and β encompass the rules of $\overline{M} \rightarrow c_i \ and \ c_i \rightarrow c_j$, respectively. Color structure implicitly encodes how colors using for constructing a color map vary from each other as well as group representative. We evaluate color structure difference by $V_s = |V_T - V_M|$, where V_T and V_M represent the color structure for the template and the target images, respectively. However, the values representing color structure difference are much larger than the color contribution difference. Hence, we perform Z-score normalization as follows:

$$c^* = \frac{c - \mu}{\delta} \tag{3}$$

where c^* is the normalized value, c is the origin value on V_s, μ and δ are the sample data mean and standard deviation, respectively. The similarity degree of the parallax relationship between the two color maps is determined by the root mean square error of the normalized values:

$$E_c = \sqrt{\frac{\sum_{i=1}^{n} |c^*|}{n}} \tag{4}$$

The color map matching effect is quantified as the energy value E, where $E = E_p + E_c$. Minimizing E is a combinatorial problem, addressing via simulated annealing approaches. Based on the target color map, an optimized matching color map is constructed from the template image. We stop iterating when the temperature drops to 0.001. Our tests set the maximum number of iterations to 100.

Brightness Adjustment

A background object of a home scene may likely comprise a simple color with brightness being adjustable, such that lighting conditions of a home scene can been taken into account. To support color migration for a background object, we allow a user to perform color selection indicating which representative color from the template image should be migrated to the target home scene. We also maintain the brightness relationship, where the brightness adjustment is done by:

$$\frac{I_t - C_t}{P_t - I_t} = \frac{I_m - C_m}{P_m - I_m} \tag{5}$$

While we migrate a color, we also adjust the brightness accordingly. As illustrated in Fig 4 (d), I_t and I_m are the average brightness of the target image and the template image, respectively. P_t is the original brightness value of the background of the target image. P_m is the adjusted background brightness after color migration.

Multi-Subgraph Color Reconstruction

Our framework involves color structure, well matching indoor home scene nature, which comprises discrete furniture items. The color migration process is supported by a matching color map in the section of Color Map, which comprises a confined set of dominant colors. On the contrary, since we apply segmentation to obtain such a color structure, representing each furniture item with a subgraph structure to support color migration, undesired holes may be induced between subgraphs. We propose a color reconstruction method to fix the problem.

As we have segmented a home scene according to the furniture settings, each target image pixel is effectively being classified to a cluster. When color migration occurs, the color of each cluster center of the target image will be replaced by an appropriate dominant color from the matching color map. This effectively offsets the center of each cluster, and that all cluster members should be updated accordingly to retain the visual representation of all home scene furniture. With this goal, we update the color of each cluster members by offsetting its value with its original distance to the cluster center before color migration. To facilitate this, the number of elements in the matching color map $\{T_1, T_2, ..., T_j\}$ of a template image and that in the target color map $\{C_1, C_2, ..., C_j\}$ must be agreed, i.e. $i = j$.

There are two main causes of the hole problem, either due to non-overlapping or partial overlapping of segmented target image regions. For holes caused by non-overlapping regions, we can fix them by identifying their existence through edge detection because such holes will appear along the boundaries of image regions. We perform this by adopting an edge detection algorithm [26]. The probability of a pixel being a boundary point is determined by the edge intensity of the pixel, which is the color value of a detected edge. Since an edge can be roughly classified as a vertical or a horizontal one, we apply the rules as in Eq 6 and Eq 7 to evaluate the possibility of an edge being holes:

Vertical:

$$\begin{cases} max\left(\phi\left(w1\right), \left(\phi\left(h2\right), \left(\phi\left(w2\right)\right) == \left(\phi\left(h2\right)\right. \\ max\left(\phi\left(w1\right), \left(\phi\left(h2\right), \left(\phi\left(w2\right)\right) \neq \left(\phi\left(h2\right)\right. \end{cases} \tag{6}$$

Horizontal:

$$\begin{cases} max\left(\phi\left(l1\right),\left(\phi\left(h2\right),\left(\phi\left(l2\right)\right) == \left(\phi\left(h2\right)\right.\right.\right. \\ max\left(\phi\left(l1\right),\left(\phi\left(h2\right),\left(\phi\left(l2\right)\right) \neq \left(\phi\left(h2\right)\right.\right.\right. \end{cases} \tag{7}$$

where $\phi\left(n_i\right)$ represents the color value of a particular image pixel as an edge pixel and n represents the set of pixels under consideration. If the max value of $\phi\left(n_i\right)$ is equal to $\phi\left(h2\right)$, the pixel of h2 is an edge pixel. Fig 7 provides a graphical illustration of example holes and their types.

Holes that are edge pixels in the image are repaired using boundary point matching. Let k is an image boundary pixel and its surrounding pixels are $\{k_t, k_b, k_l, k_r\}$. Color similarity $(min\left(E\right))$ between the pixel of the same position in the original target image and its surrounding pixels is calculated, i.e., $\left\{k_i \overset{E_{min}}{\rightarrow} k, i \in (l, r, t, b)\right\}$. The algorithm obtains the pixel position with the most similar color to the hole color and fills the hole in the reconstructed target image. In contrast, a non-edge hole will be repaired by the mean color of pixels $\{k_t, k_b, k_l, k_r\}$.

Experiment Results

Our Results

Our framework is unique as besides considering color structure to assist color migration, it also incorporate user interaction to allow user expectation to be faithfully expressed during the process. Here we present our results.

Color Migration of Furniture: Color change to individual furniture items could be critical as a user may want to explicitly decide their coloring in an interior decoration process. We therefore allow users to interactively select a region of interest from the template image, indicating how the coloring of a furniture item will be changed. As shown in Fig 8, color migration of a target furniture item I can be performed with different regions of interest, as indicated as T1, T2 and T3 in the template image T. The corresponding color migration results are R1, R2 and R3, respectively.

Natural Scenery as Template: Using natural scenery as template image for color migration is challenging, as it is difficult to obtain a satisfactory result due to their complication in image content and coloring. We demonstrate our results with using natural scenery as the template images to express user coloring expectation. As shown in Fig 9, with each of three different input home scenes (I), we apply two different template images (T) to generate color migration results (R1, R2 and R3), where R1, R2 and R3 are obtained by selecting different regions of interest. Results show that dominant colors from template images can always be satisfactorily migrated to home scene images and the visual appearance of all furniture items can still be properly retained without any distortion.

Indoor Home Scene as Template: It is quite natural to use the coloring design of another home scenery image to express how color change should be happened for an indoor environment. As in Fig 10, given an input home scene (I), we apply two different template home scene images (T) and obtain two results (R) accordingly. Particularly, user interaction is also involved to indicate some specific regions of interest for customizing color migration.

Comparisons

We have demonstrated that sensible and customizable results can be generated from our framework. In this section, we compare the performance between our framework and some existing work. We also discuss the limitations of our work.

Methods: Fig 11 shows color migration results generated by our framework and relevant existing work based on three different input scenes and three different template images. The first row shows input home scene images (I), each of them will go through color migration by a specific template image of natural scenery (T) as shown in the second row. Results generated by our method (OU) are presented in the third row. Results by existing methods [20], [27], [28], [11] labeled as R, X, F, H are presented in the other rows, respectively. In general, our framework can generate faithful results, since color changes are essentially be done based on scene objects (furniture items). In contrast, color migration results generated from all existing work we compared exhibit artificial changes [12], including gradual color changes over the ceiling and global change in overall image tone. These color change effects are not practical for interior coloring design. We further compare the image quality produced by all methods based on PSNR and SSIM as shown in Table 1. We have highlighted the top two results under each column. Obviously, our method performs well in most cases. Although method [11] seems performing well for scene 1 and 2, the corresponding visual outputs as presented in Fig 11 clearly show inferior quality than outputs generated by our method.

User Study against Designer's Work: A user study was conducted to evaluate our work according to their intuitive visual perception. We invited 20 users to evaluate 5 sets of images (S1 to S5). Each image set consisted two parts of coloring results. One part was generated by performing color migration with our framework (OURS), while the other part contained color transformation results produced by interior decoration designers (ARTS). Participants described their perception on these results using a five-point (1-5) rating system. We depict the user study results by averaging user ratings separately for these two parts of coloring results. As in Fig 12, results produced by our framework are mostly comparable with those produced by designers. In S1, our generated output was better perceived by participants comparing with the designer output.

Computational Performance: Our framework was implemented by MATLAB running on a computer with an Intel Core i5 3.30GHz CPU and 16GB RAM. The preparatory work of interactive segmentation took about 1 hour for each image. The color migration operation with our framework can typically be finished within about 5 minutes per image.

User Study against Different Template Images: To study user perception on color migration with different template images, we selected 3 home scene images and 12 template images to evaluate the satisfaction of our color migration framework. Each scene was paired with each template image 10 times (i.e., migration was performed 10 times for each pairing), providing 360 results by running our framework. Each result was labeled as ideal or not ideal. We invited 50 people to test, and calculated the average of their evaluations. According to the evaluation results, our work can achieve an ideal color migration with the probability of 71%. Fig 14 shows the histogram of satisfaction according to template images of T1 to T12, home scene images S1 to S3 as the targets for color migration. While most of the results are generally satisfactory, we still receive less favorable results, particularly when T9 and T5 were used as the template images, since they contained strong colors.

Limitations: Our work can produce faithful color migration in most cases. However, our framework occasionally produce less satisfactory outputs. As shown in Fig 13, we may generate outputs with strong coloring, which may not be favorable for general users. The main reason for this results is that the simulated annealing algorithm, which we have applied to optimize the color migration, introduces randomness. Consequently, undesirable results may be generated sometimes given the same template image is used. Moreover, if a template image is dominated by very strong or high-contrast colors, it is unavoidable that the color migration results will still contain coloring along these lines. This may make sense because the template image represents a user's coloring expectation.

Conclusion

We have introduced a new color migration framework, allowing natural scenery to be used as the template for users to express their coloring expectation. We have also incorporated user intervention to customize color migration results. We have developed a hierarchical color structure to match with native home scene composition, i.e., natively forming by collocated furniture, we can produce faithful and practical color migration results. In future work, we like to allow using multiple template images to govern color migration. We also like to investigate how machine learning can assist home scene segmentation and coloring.

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Input Coloring 1 Coloring 2

Figure 1: Input image (left). Our results (Coloring 1 and 2) based on natural and interior scenery templates, respectively.

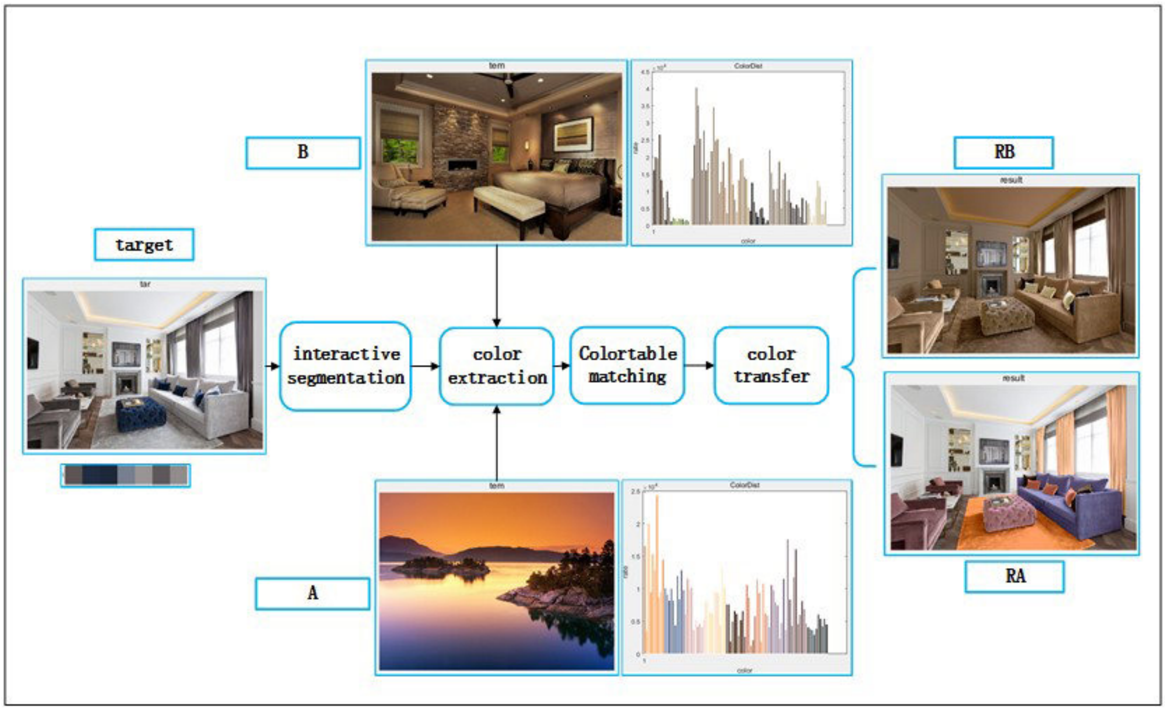


Figure 2: Our color migration framework.

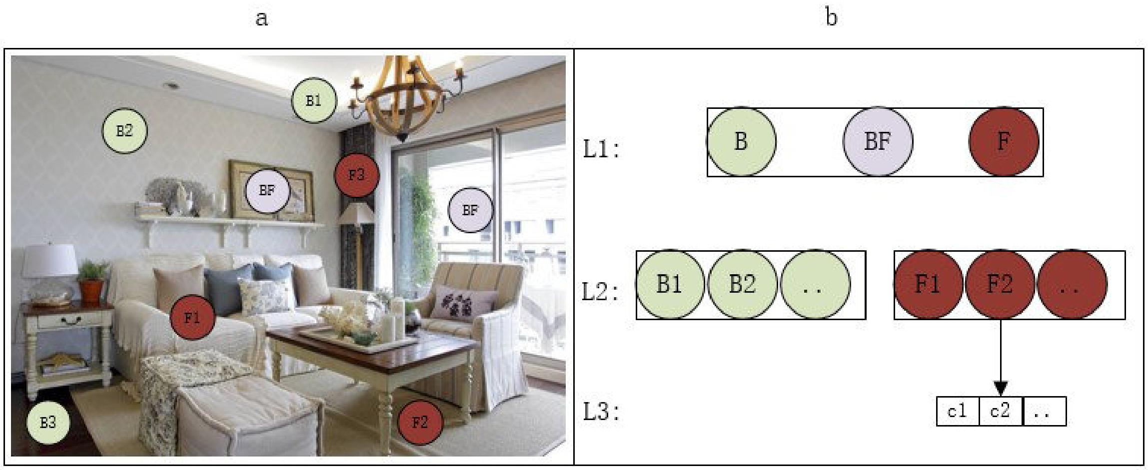
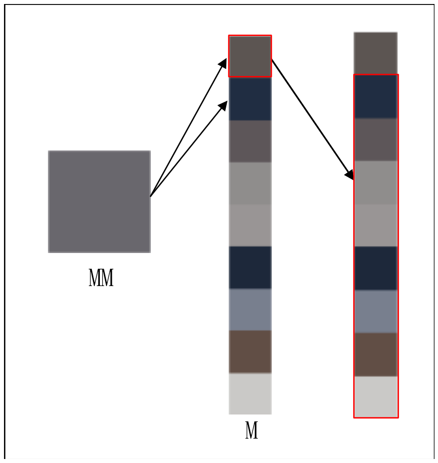
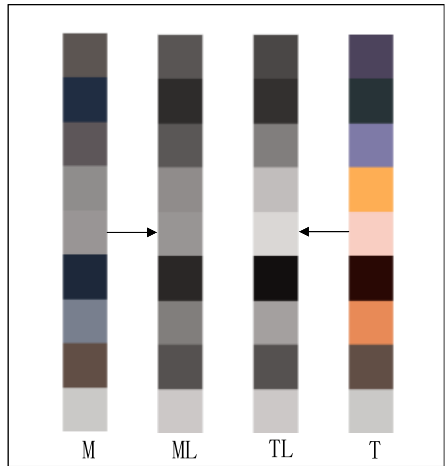


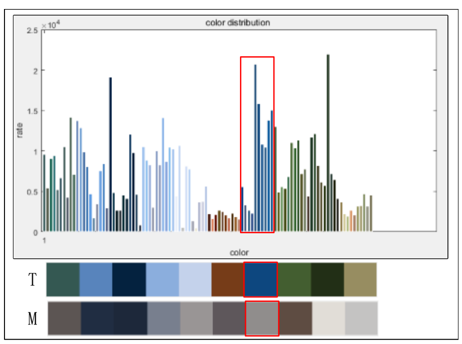
Figure 3: Color structure relationship.



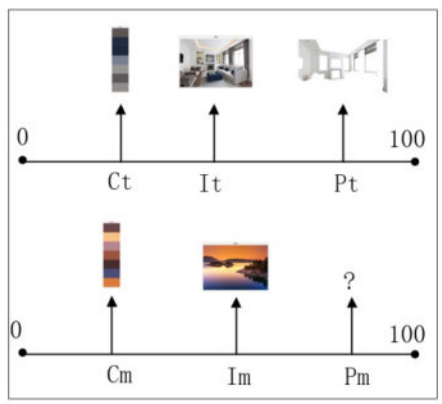
(a) Color relationship



(b) Luminance map



(c) Matching color table



(d) Brightness adjustment

Figure 4: Color table strategy

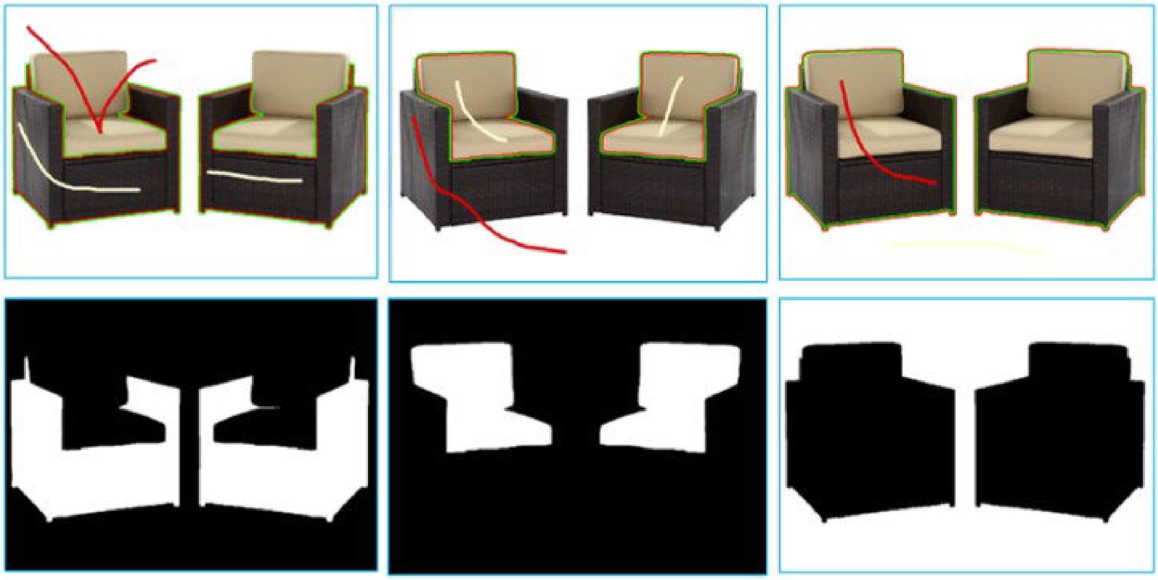


Figure 5: Interactive segmentation.

Figure 6: Color extraction comparison.

Figure 7: Example of holes (left); Scene edge detection (middle); Hole judgment diagrams (right), for vertical (A) and horizontal (B) holes, respectively.

Figure 8: Color migration of furniture based on user interaction.

Table 1: Performance comparison by PSNR and SSIM metrics.

Method	Scene 1		Scene 2		Scene 3	
	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR
OU	0.89	**31.22**	**0.82**	**27.34**	**0.94**	**32.19**
R	0.88	23.09	0.68	22.56	0.83	23.91
X	**0.91**	23.97	0.67	22.76	0.79	25.36
F	0.8	23.063	0.65	22.32	**0.84**	**25.67**
H	**0.94**	**26.36**	**0.85**	**36.4**	0.68	24.69

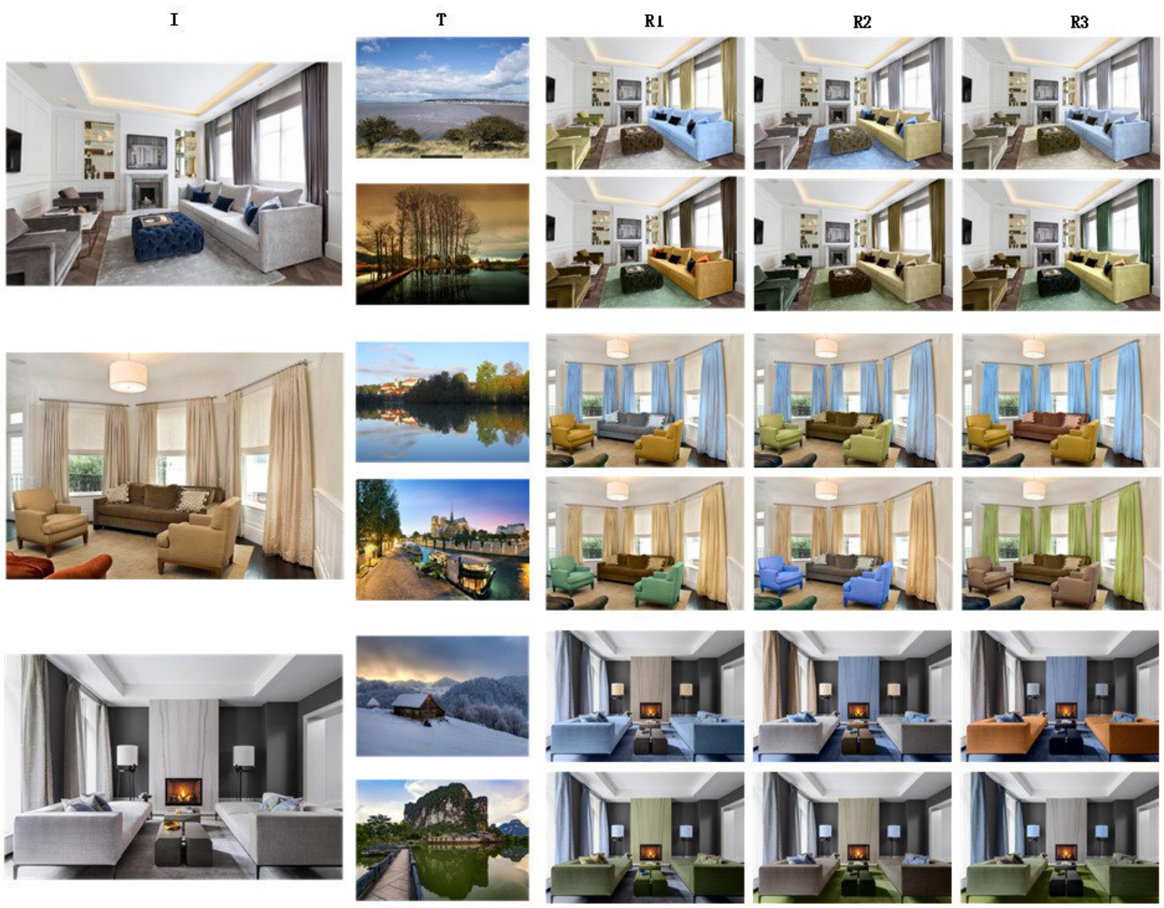


Figure 9: Color migration with natural scenery as template images.

Figure 10: Color migration by picking coloring from other home scenes.

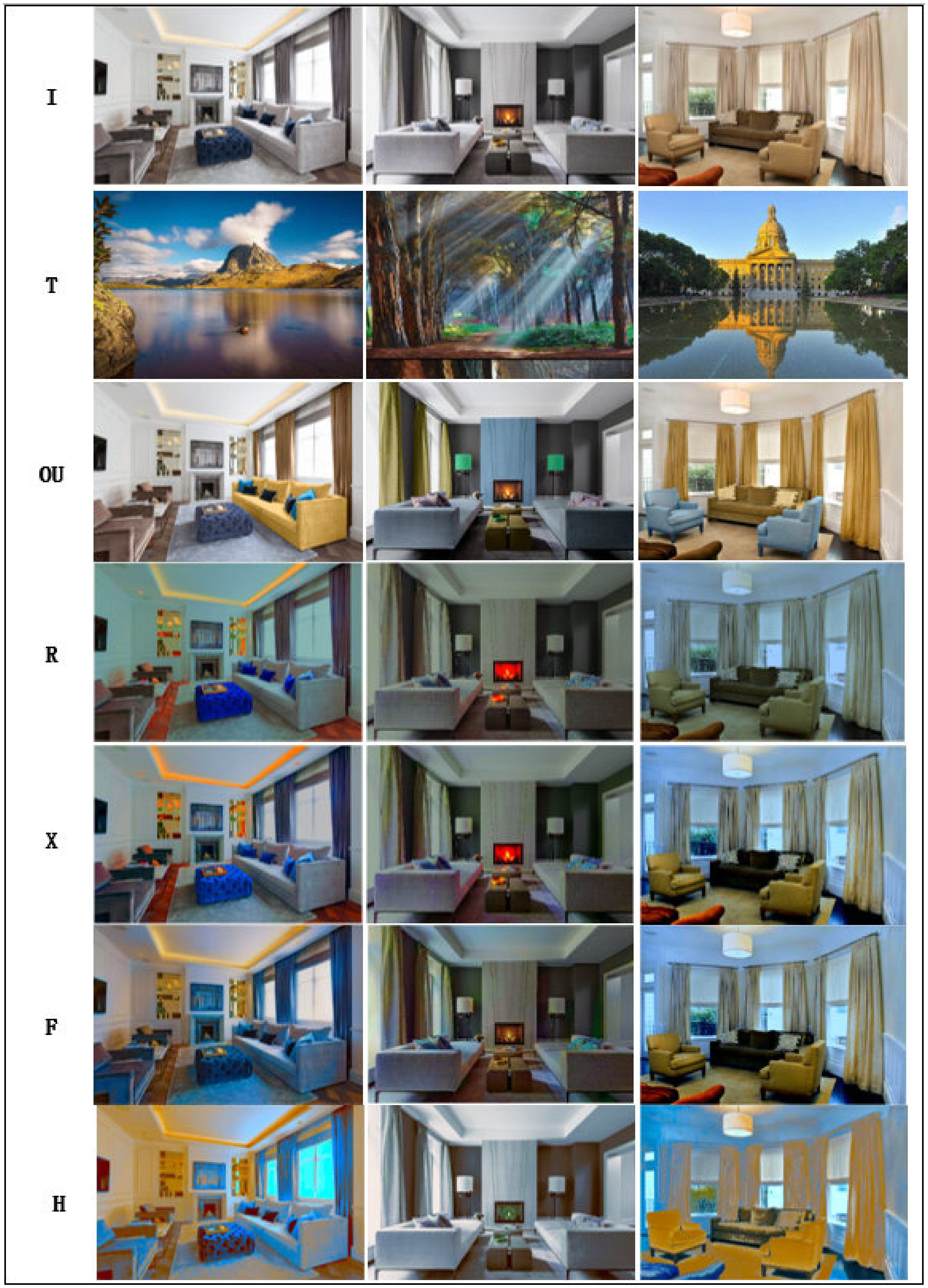


Figure 11: Comparison of color migration by different methods.

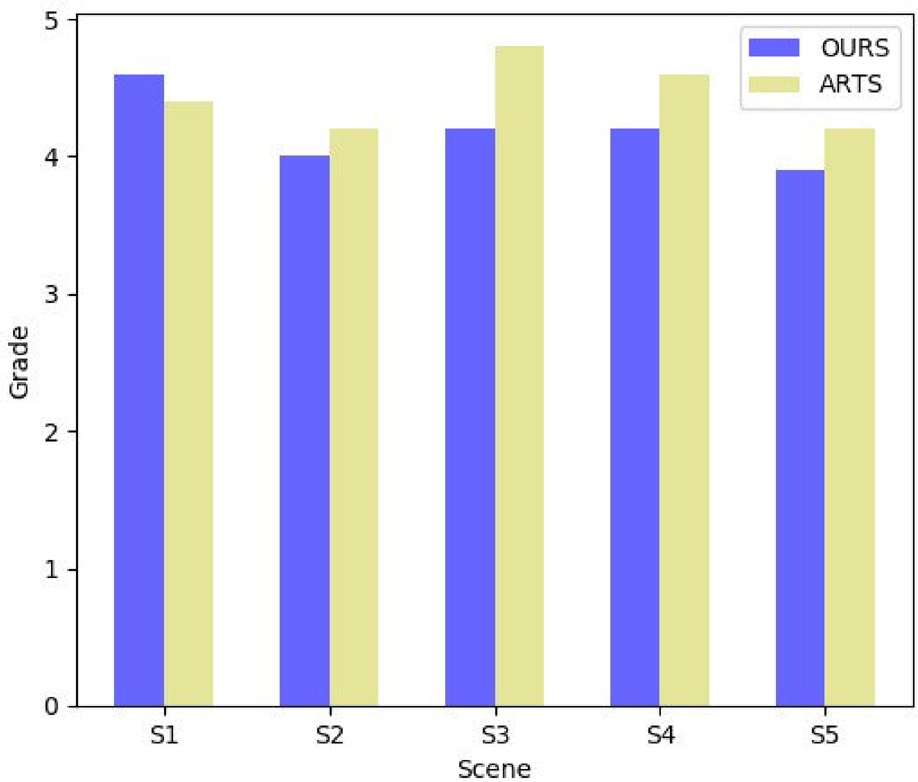


Figure 12: Comparison of our and designer's outputs.

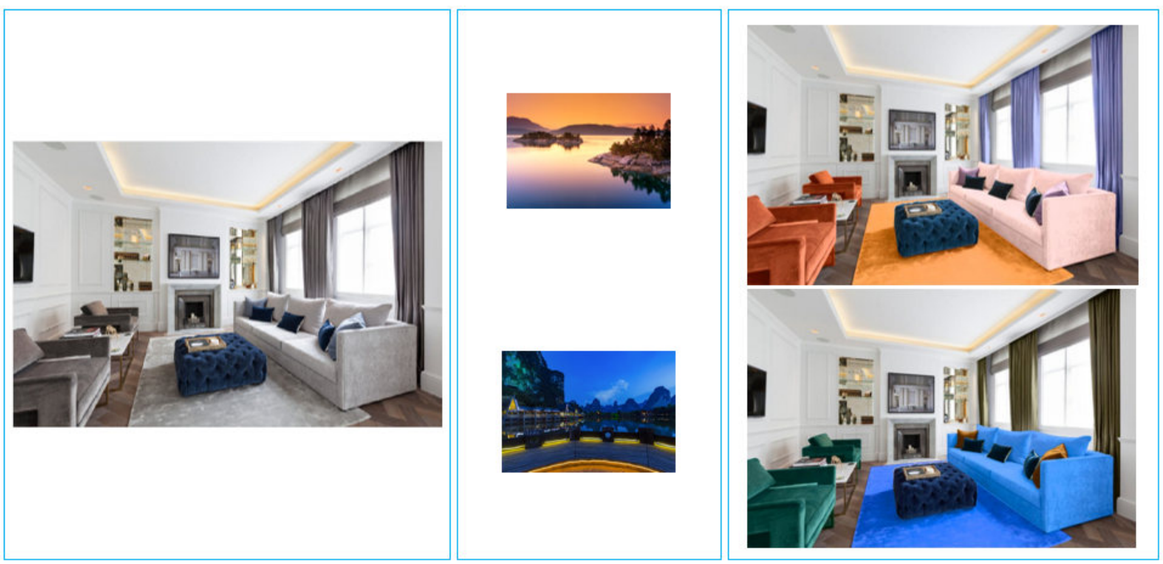


Figure 13: Examples of undesirable color migration results.

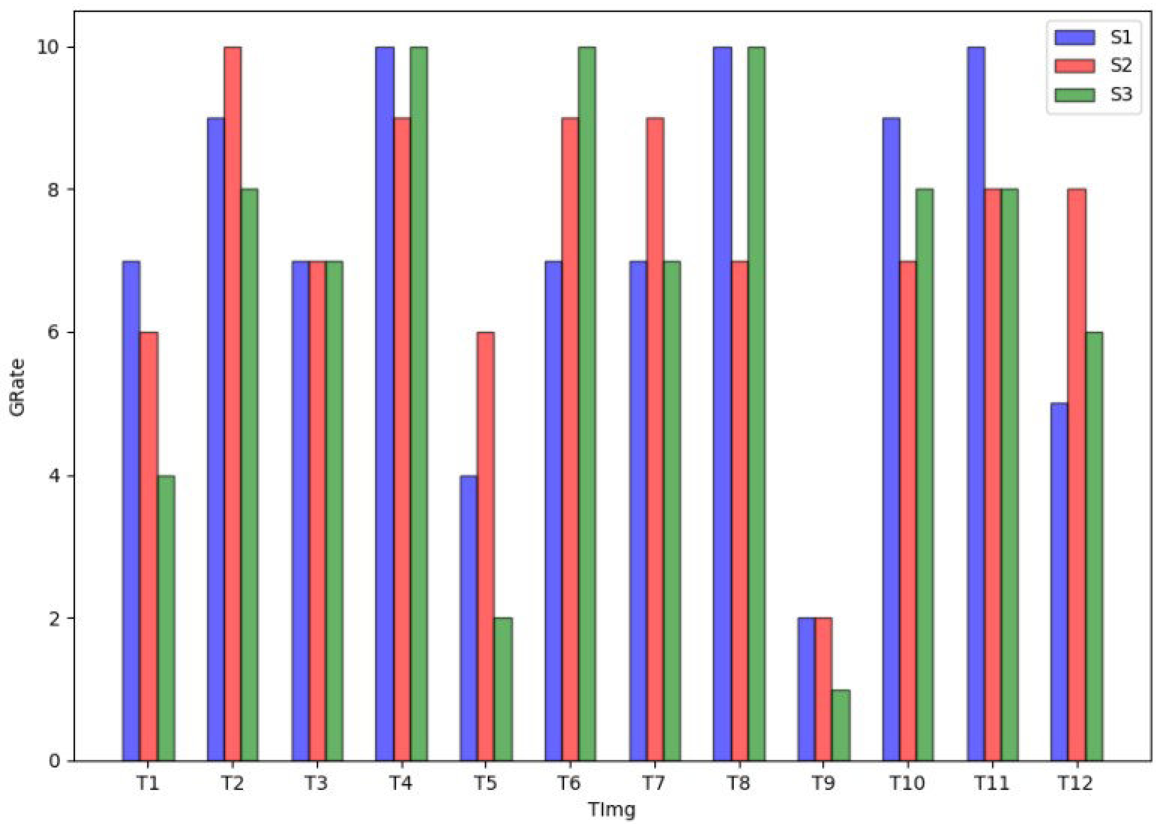


Figure 14: Migration effect distribution histogram.