Image Recoloring For Home Scene

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ABSTRACT

Indoor home scene coloring technology is a hot topic for home design, helping users make home coloring decisions. Image based home scene coloring is preferable for e-commerce customers since it only requires users to describe coloring expectations or manipulate colors through images, which is intuitive and inexpensive. In contrast, if home scene coloring is performed based on 3D scenes, the process becomes expensive due to the high cost and time in obtaining 3D models and constructing 3D scenes. To realize image based home scene coloring, our framework can extract the coloring of individual furniture together with their relationship. This allows us to formulate the color structure of the home scene, serving as the basis for color migration. Our work is challenging since it is not intuitive to identify the coloring of furniture and their parts as well as the coloring relationship among furniture. This paper presents a new color migration framework for home scenes. We first extract local coloring from a home scene image forming a regional color table. We then generate a matching color table from a template image based on its color structure. Finally we transform the target image coloring based on the matching color table and well maintain the boundary transitions among image regions. We also introduce an interactive operation to guide such transformation. Experiments show our framework can produce good results meeting human visual expectations.

CCS CONCEPTS

• **Human-centered computing** → *Scenario-based design*; *Interaction design theory, concepts and paradigms*;

KEYWORDS

Indoor home scene, coloring expectation, color structure, color migration, interactive operation.

1 INTRODUCTION

Image is a most popular and cost-effective type of media for e-commerce applications to present their products. By presenting images of various home scene coloring design, interior decorators can effectively convey ideas of good designs and pleasing color combinations to their customers. Typically, a design comprises style and color, determining how well a set of collocated furniture goes well with each other aesthetically. Human perception on object attractiveness is mainly influenced by color [Peters 2007]. While different color combinations impose distinct effects to each person, they also implicitly define home style. In general, style, color and furniture location forms determining factors of how a person perceives home scene design.

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 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, image based color migration methods require extracting meaningful regions (or objects) in order to work out region based local coloring. This is typically challenging since regions or their boundaries are not natively defined in an image. To produce aesthetic coloring designs, color structure transformation is also required for both 3D model and image based methods. Existing methods often perform global color migration without considering spatially local color properties and interactions, leading to undesirable local color distortion. In addition, the relationship between colors and furniture parts in a home scene image is difficult to establish.

Our work presents a novel framework for migrating colors from a template image of natural or interior scenery, which represents user coloring expectation (or design), to a home scene image. We also involves user intervention to assist object segmentation, addressing the color distortion problem. Judging from intuitiveness and simplicity, our work is favorable to both professional interior

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decorators and non-professional users. Our main contributions include: 1) a color migration framework for home scene images based on template coloring transformation, 2) meaningful regional color structure extraction, 3) new color table matching strategy, and 4) multi-subgraph based color reconstruction.

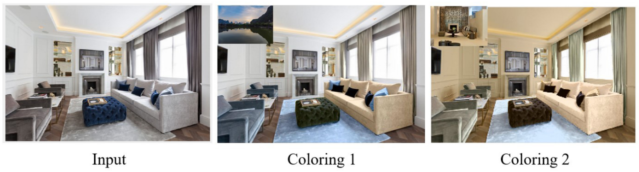


Figure 1: Input image (left). Our results (Coloring 1 and 2) based on natural and interior scenery templates, respectively.

2 RELATED WORK

Home scene color processing spans multiple directions, including color organization processing, dominant colors extraction, color table strategy, and color transfer. Existing work focuses on processing a home scene according to certain color schemes rather than migrating colors of a home scene image by observing their spatial relationships.

2.1 Color Organization Processing

Color organization of indoor home scenes is an important research topic in computer graphics and vision, including 3D model based [Chen et al. 2016, 2015; Zhang et al. 2017; Zhu et al. 2017] or image based [Nguyen et al. 2014; Tanaka et al. 2010; Wang et al. 2012] approaches. 3D model methods cannot be directly adopted to support color migration for home scene images since they rely on pre-defined home scene object (or furniture) definitions, which are not available in images. Regarding existing work, Wang et al. [Wang et al. 2012] proposed an emotion-based image colorization system, which required 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. [Nguyen et al. 2014; Tanaka et al. 2010] 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 are categorized as local color transformation, which is a challenging problem.

2.2 Dominant Colors Extraction

The overall perceived hue of an image can be well represented by some dominating hues. Examining dominant colors is popularly done by color clustering [Bezdek 1981; Chang et al. 2015; Weeks and Hague 1997]. 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 theme. Lin et al. [Lin and Hanrahan 2013] used a regression model to train a model for characterizing human-extracted themes and performed image theme extraction. Such an approach processed image coloring globally, failing to account for color relationships among furniture items.

2.3 Color Table Strategy

Several online communities devoted to share and create color themes, including Adobe Kuler [a13 [n. d.]] and COLOURloverss [a14 [n. d.]]. Most of their themes are extracted from images and use a small fixed number of colors, making them cannot be used directly to transform 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. [Birren 1969; Itten 1973] have confirmed that different color combinations impose distinct feelings for each human viewer. Color harmonic model [Ou and Luo 2006] was then developed to evaluate whether a color pair is harmonic. This evaluation was only valid within a controlled environment, not being generalizable. [Cohen-Or et al. 2006] 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, [O'Donovan et al. 2011] proposed a data-driven model to evaluate the harmony of color combinations by scoring 5 colors from a color group. Both 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.

2.4 Color Transfer

Color transformation reconstructs target image coloring by some mapping rules. [Reinhard et al. 2001] 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 [Tai et al. 2005] was performed by matching probabilistically segmented color regions and inter-region smoothness against the template and target images, where spatial correspondence among regions were optionally enforced. Some color transfer methods use nonlinear histogram matching [Neumann and Neumann 2005; Papadakis et al. 2011; Pouli and Reinhard 2011] to handle global color migration. Alternatively, [Chang et al. 2015] 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 to be 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 the scene objects, local color distortion may be resulted when they are adopted for home scene color transfer.

3 OVERVIEW

Our framework accounts for both home scene content and human perception characteristics:

3.1 Color Guidance

To allow faithful transformation of user expectation into a home scene coloring design, we formulate three constraints to guide color migration: 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.

3.2 Interactivity

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

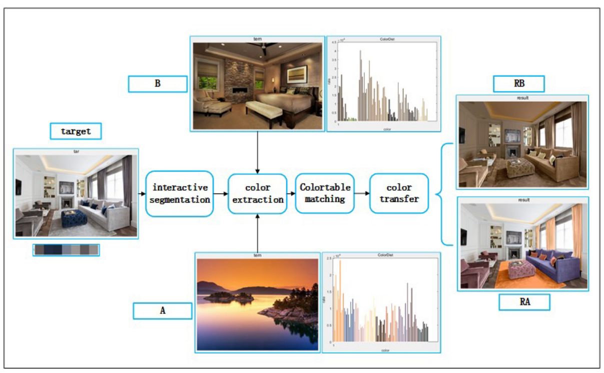


Figure 2: Our color migration framework.

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 this 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. Algorithm 1 shows how the above workflow is implemented.

Table 1: Algorithm 1

Algorithm 1:
Begin: Input:target I,template T;
Phase 1: Regional main color extraction
//Target image subgraph segmentation
segmentation(I)->sub_I;
//color table extraction
[tarC,temC]=extraction(sub_I,T);
//Template image color table extension
NtemC=expand (temC);
Phase 2: Color strategy
interact;//color interactive choice
//Foreground color chart generation
For Temperature conditions(t>0.001) do
For The number of iterations do
Tmp=Adjust(create(NtemC));
Calculated(tarC, Tmp);
End For
//update the temperature
F_C= Tmp;
Update t;
End For
//Background part brightness adjustment
B_C ->Adaptive(I,T, F_C);
Phase 3: Multi-Subgraph Color Reconstruction
NI=combination (transfer(sub_I,F_C, B_C));

4 BASIS OF HOME SCENE COLORING

4.1 Color Features

Uniquely, our method allows coloring design to be expressed by natural or indoor scenery, where their color transitions are gradual and discrete, respectively. Taking human perception in account, it is natural to divide a home scene into foreground and background objects. Foreground objects usually comprise furniture, placing in certain designated indoor positions. Their placement and coloring are local, representing user design preferences. Examples include table and chair (movable), or window and door (at fixed position). Background objects refer to fixed house parts, such as wall and floor, with colors widely spanning across a significant scene portion. For a home scene, there may be some restricted features, including outdoor scenery, indoor plants, collectables, etc., with unchangeable coloring, which should be excluded from color migration.

4.2 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.

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

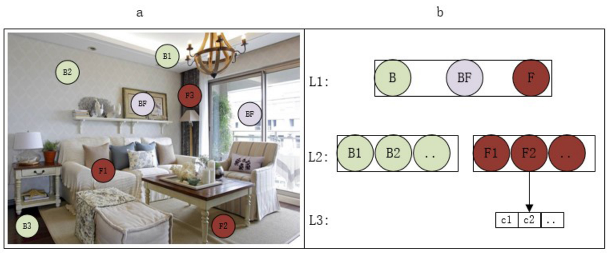


Figure 3: Color structure relationship.

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.

4.3 Color Map

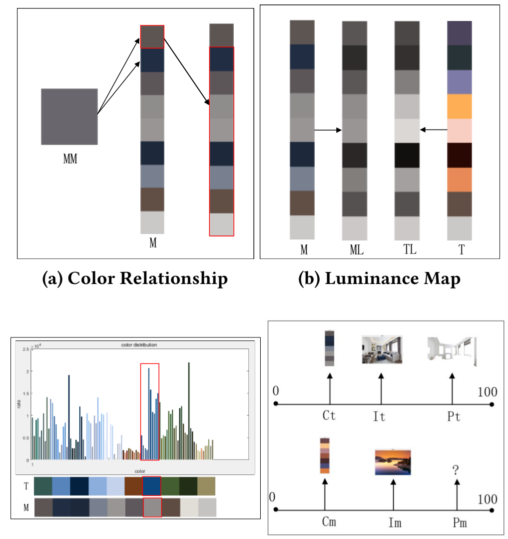
Color map comprises a finite number of colors representing image content. Existing work store their color clustering results as a color map. Replacing some colors in a color map can change image tone or style. This operation generally cannot accommodate color change to regional image contents, due to lacking scene structure correspondence. To maintain color relationship, we argument color map with a two-level color relationship. For a color map $M = \{c_1, c_2, ..., c_n\}$, we average all color items c_n to produce a mean color MM, the color map representative. As shown in Fig 4 (a), the first level color relationship is modeled by the distances between MM and each color map element, 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. Rule (1) shows the metric formulating the two-level color relationship. We evaluate color distance by using Euclidean distance under the standard CIELab color space.

$$\begin{cases} mean\,(M) \longrightarrow c_i & i, j \in n \text{ } and \text{ } i \neq j \\ c_i \longrightarrow c_j & i, j \in n \text{ } and \text{ } i \neq j \end{cases} \tag{1}$$

5 OUR APPROACH

5.1 Regional Dominant Color Extraction

5.1.1 User Assisted Segmentation. To faithfully transform user expectation into home scene coloring design, we account for the scene furniture and their color relationship. Despite native color clustering may extract such information, noisy results (Fig 6, middle) are likely obtained for an input image (Fig 6, left), due to color or illumination variation appearing on individual furniture item. To properly extract dominant furniture coloring, we incorporate user intervention to assist color segmentation. We adopt an interactive segmentation algorithm [Price et al. 2010] 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 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 (Fig 5, top-left), foreground and background objects (Fig 5, bottom-left) can be extracted, respectively. Other sub-diagrams of Fig 5 depicts



(a) Color Relationship **(b) Luminance Map**

(c) Matching Color Table **(d) Brightness Adjustment**

Figure 4: Color table strategy

how different stroke inputs generate different foreground and background objects. Allowing multiple stroke drawing interactions can further assist complicated scene or furniture item partitioning.

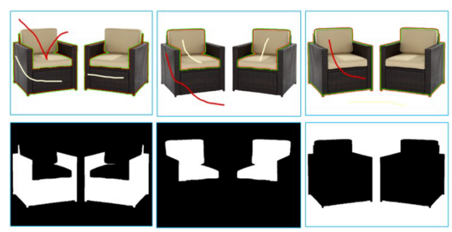


Figure 5: Interactive segmentation.

Figure 6: Color extraction comparison.

5.1.2 Color Extraction: After segmentation, a hierarchical color structure can be generated. For each furniture item, a subgraph is generated to represent color parts constitute 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 $C = \{c_1, c_2, ..., c_k\}$. An example of our color extraction result is shown in Fig 6 (right). Our method explicitly works out the correlation between home scene structure and colors. Alternatively, if only simple color clustering results (e.g. Fig 6, middle) are used for color replacement, confusing results may be produced. 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.

5.2 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.

5.2.1 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.

5.2.2 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.

5.2.3 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.

5.2.4 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 $mean\ (M) \to c_i\ and\ c_i \to c_j$, 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.

5.2.5 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:

$$\frac{It_l - Ct_l}{Pt_l - It_l} = \frac{Im_l - Cm_l}{Pm_l - Im_l} \tag{5}$$

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

5.3 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 (ref. Section 5.2.1), 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 $\left\{T_1, T_2, ..., T_j\right\}$ of a template image and that in the target color map $\left\{C_1, C_2, ..., C_j\right\}$ 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 [Xu et al. 2012]. 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:

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

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., $\left\{k_i \overset{E_{min}}{\longrightarrow} k, i \in \left(l, r, t, b\right)\right\}$. 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 $\{k_t, k_b, k_l, k_r\}$.

6 EXPERIMENT RESULTS

6.1 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.

6.1.1 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 8, 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.

6.1.2 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 9, 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.

6.2 Comparisons

6.2.1 Methods. Fig 10 shows color migration results generated by our framework and relevant existing work. Given an input home scene image (I), a template image of natural scenery (T) is used to guide color migration. While the results from our method is labeled as OU, the results from [21, 35, 36] are labeled as R, X, F, respectively. Each column shows the inputs and outputs based on different input home scene image and template image. In general, our framework can generate faithful results, as 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, e.g. with gradual color changes over the ceiling, and the overall image tone has been globally changed. All these color change effects are not practical for interior coloring design.

6.2.2 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

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

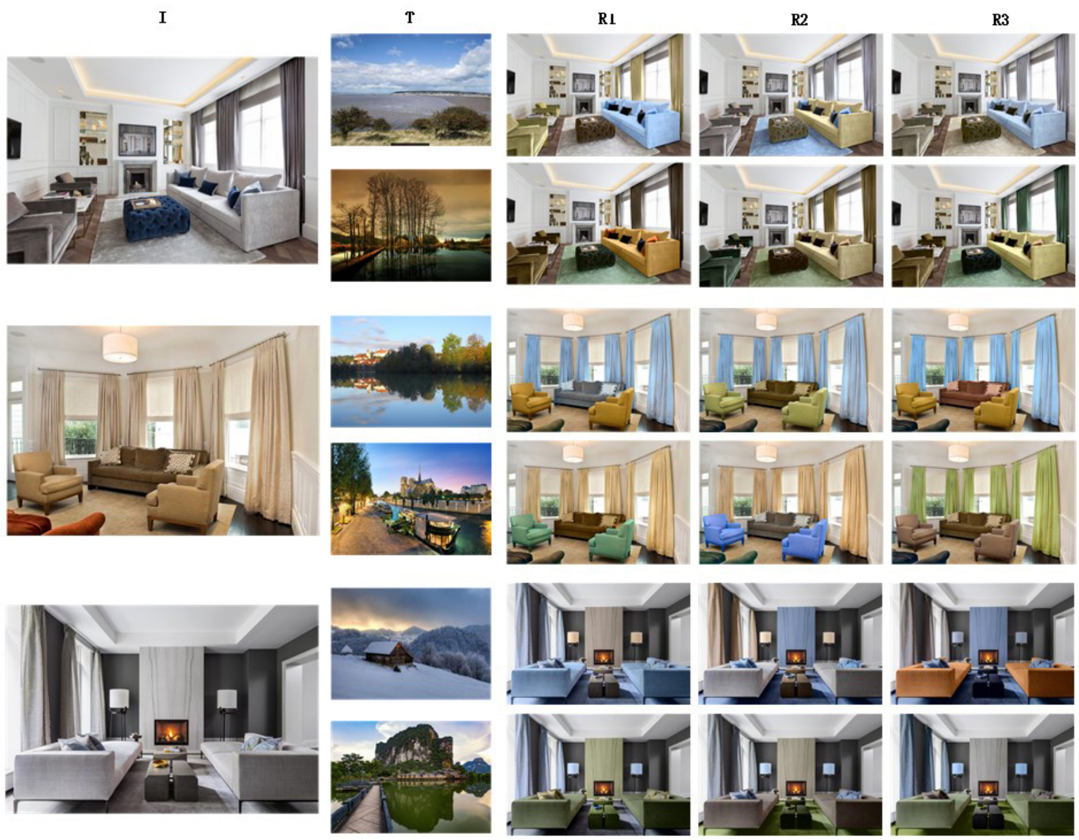


Figure 8: Color Migration with Natural Scenery as Template Images.

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 11, 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.

6.2.3 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.

Figure 9: Color Migration by Picking Coloring from Other Home Scenes.

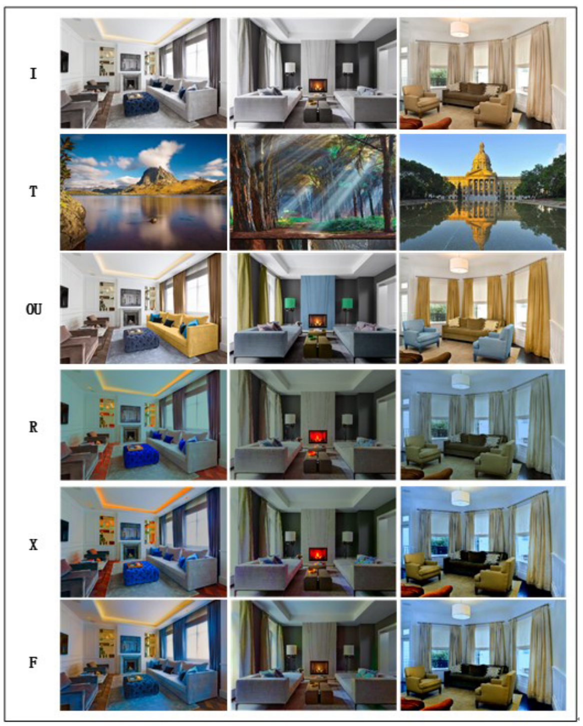


Figure 10: Comparison Results.

7 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 also allow user invention to be involved to customize color migration results. Because 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.

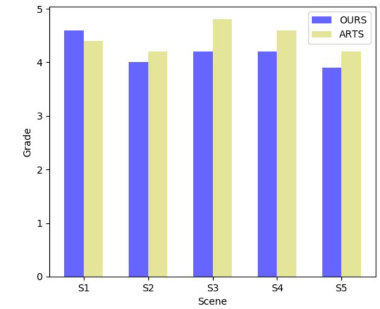


Figure 11: Comparison of Our and Designer's Outputs.

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REFERENCES

[n. d.]. Adobe Kuler. [Online]. Available: http://kuler.adobe.com. ([n. d.]).

[n. d.]. Colourlovers. [Online]. Available: http://www.colurlovers.com. ([n. d.]).

James C Bezdek. 1981. Objective Function Clustering. In *Pattern recognition with fuzzy objective function algorithms*. Springer, 43–93.

Faber Birren. 1969. A grammar of color, a basic treatise on the color system of Albert H. Munsell. (1969).

Huiwen Chang, Ohad Fried, Yiming Liu, Stephen DiVerdi, and Adam Finkelstein. 2015. Palette-based photo recoloring. *ACM Transactions on Graphics (TOG)* 34, 4 (2015), 139.

Guangming Chen, Guiqing Li, Yongwei Nie, Chunhua Xian, and Aihua Mao. 2016. Stylistic indoor colour design via Bayesian network. *Computers & Graphics* 60 (2016), 34–45.

Kang Chen, Kun Xu, Yizhou Yu, Tian-Yi Wang, and Shi-Min Hu. 2015. Magic decorator: automatic material suggestion for indoor digital scenes. *ACM Transactions on Graphics (TOG)* 34, 6 (2015), 232.

Daniel Cohen-Or, Olga Sorkine, Ran Gal, Tommer Leyvand, and Ying-Qing Xu. 2006. Color harmonization. In *ACM Transactions on Graphics (TOG)*, Vol. 25. ACM, 624–630.

Johannes Itten. 1973. *the art of Color: the subjective experience and objective rationale of Color. translated by ernst van haagen.* Van Nostrand Reinhold.

Sharon Lin and Pat Hanrahan. 2013. Modeling how people extract color themes from images. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 3101–3110.

László Neumann and Attila Neumann. 2005. Color style transfer techniques using hue, lightness and saturation histogram matching. In *Computational Aesthetics*. Citeseer, 111–122.

Rang MH Nguyen, Seon Joo Kim, and Michael S Brown. 2014. Illuminant Aware Gamut-Based Color Transfer. In *Computer Graphics Forum*, Vol. 33. Wiley Online Library, 319–328.

Peter O'Donovan, Aseem Agarwala, and Aaron Hertzmann. 2011. Color compatibility from large datasets. In *ACM Transactions on Graphics (TOG)*, Vol. 30. ACM, 63.

Li-Chen Ou and M Ronnier Luo. 2006. A colour harmony model for two-colour combinations. *Color Research & Application* 31, 3 (2006), 191–204.

Nicolas Papadakis, Edoardo Provenzi, and Vicent Caselles. 2011. A variational model for histogram transfer of color images. *IEEE Transactions on Image Processing* 20, 6 (2011), 1682–1695.

Gabriele Peters. 2007. Aesthetic primitives of images for visualization. In *Information Visualization, 2007. IV'07. 11th International Conference.* IEEE, 316–325.

Tania Pouli and Erik Reinhard. 2011. Progressive color transfer for images of arbitrary dynamic range. *Computers & Graphics* 35, 1 (2011), 67–80.

Brian L Price, Bryan Morse, and Scott Cohen. 2010. Geodesic graph cut for interactive image segmentation. In *Computer Vision and Pattern Recognition (CVPR), 2010 IEEE Conference on.* IEEE, 3161–3168.

Erik Reinhard, Michael Adhikhmin, Bruce Gooch, and Peter Shirley. 2001. Color transfer between images. *IEEE Computer graphics and applications* 21, 5 (2001), 34–41.

Yu-Wing Tai, Jiaya Jia, and Chi-Keung Tang. 2005. Local color transfer via probabilistic segmentation by expectation-maximization. In *Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on*, Vol. 1. IEEE, 747–754.

Go Tanaka, Noriaki Suetake, and Eiji Uchino. 2010. Color transfer based on normalized cumulative hue histograms. *Journal of Advanced Computational Intelligence and Intelligent Informatics* 14, 2 (2010), 185–192.

Xiao-Hui Wang, Jia Jia, Han-Yu Liao, and Lian-Hong Cai. 2012. Affective image colorization. *Journal of Computer Science and Technology* 27, 6 (2012), 1119–1128.

Arthur Robert Weeks and G Eric Hague. 1997. Color segmentation in the HSI color space using the K-means algorithm. In *Nonlinear Image Processing VIII*, Vol. 3026. International Society for Optics and Photonics, 143–155.

Li Xu, Qiong Yan, Yang Xia, and Jiaya Jia. 2012. Structure extraction from texture via relative total variation. *ACM Transactions on Graphics (TOG)* 31, 6 (2012), 139.

Suiyun Zhang, Zhizhong Han, Ralph R Martin, and Hui Zhang. 2017. Semantic 3D indoor scene enhancement using guide words. *The Visual Computer* 33, 6-8 (2017), 925–935.

Jie Zhu, Yanwen Guo, and Han Ma. 2017. A Data-driven Approach for Furniture and Indoor Scene Colorization. *IEEE transactions on visualization and computer graphics* (2017).