Color Transfer for Images: A Survey

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High-quality image generation is an important topic in digital visualization. As a sub-topic of the research, color transfer is to produce high-quality image with ideal color scheme learned from the reference one. In this paper, we investigate the mainstream methods of color transfer to provide a survey which introduces the related theories and frameworks. Such methods can be concluded into three categories: statistical color transfer; semantic-based color transfer; color transfer for special target. For these mainstream technical routes, we discuss the related research background, technical details, and representative methods. We also exhibit some new trends of the topic according to the recent progress. Based on the comparisons, we discuss the unsolved issues of color transfer and potential solutions in future work.

CCS Concepts: • **Computing methodologies** → **Image processing**; **Computational photography**.

Additional Key Words and Phrases: Color Transfer, color mapping, image enhancement, lighting optimization.

ACM Reference Format:
Chenlei Lv, Dan Zhang*, Shengling Geng, Zhongke Wu, and Hui Huang. 2023. Color Transfer for Images: A Survey. 1, 1 (November 2023), 28 pages. https://doi.org/10.1145/nnnnnnn.nnnnnnn

1 INTRODUCTION

Following new requirements of digital imaging technology, many researchers focus on intelligent algorithms to improve the quality of visualization for computer vision and image processing. Such algorithms are designed to generate high-quality images with simple, even incomplete input. The related works include image enhancement, completion, super resolution, style and color transfer, etc. As a sub-topic, color transfer has been researched for decades, which is to endue better color scheme for images while keeping the content. An instance is shown in Fig. 1. With the verified color scheme of reference image, the quality of source one can be improved by color transfer. Some related tools have been successfully applied in photo post-processing software and camera system.

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This research is supported in part by a grant from National Natural Science Foundation of China (62102213, 62172247); Young and middle aged scientific research foundation of Qinghai Normal University (2021004); Natural Science Youth Foundation of Qinghai Province(No.2023-ZJ-947Q).

XXXX-XXXX/2023/11-ART $15.00
https://doi.org/10.1145/nnnnnnn.nnnnnnn

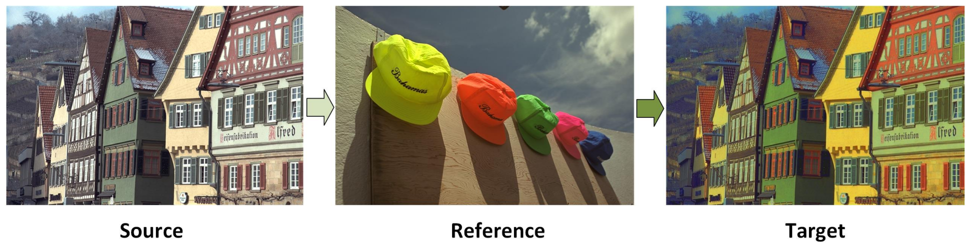

Fig. 1. An instance of color transfer by [88]. According to a reference image, the source image can be transferred to the target one with better colorization.

In traditional way, some color transfer methods ([64][38]) are designed based on manual input. Such methods require users to provide some specific operations to generate new color information. For instance, different objects in image should be specified for contrast enhancement. Some parameters should be adjusted, including color saturation, white balance, highlight area, etc. With a series of complex operations, a new image with aesthetic and natural color information can be obtained. Obviously, the methods require professional experience of users and lack friendly interaction. Such drawbacks limit the popularity of related technologies. Therefore, such methods are not considered in this survey.

The automatic color transfer methods without artificial adjustment can be concluded into several categories: statistical color transfer, semantic-based color transfer, and special target color transfer. Statistical color transfer methods attempt to compute a color mapping between different images based on statistical color distribution. Such methods don't consider semantic correspondence. Semantic-based color transfer methods are proposed to construct accurate semantic correspondence from images to generate more reasonable color scheme. However, the performance of semantic correspondence detection is not stable. It is affected by the lighting condition and poses of related objects between images. Following the development of deep learning, some researchers introduce deep feature analysis for the semantic-based color transfer task. Deep feature-based color transfer methods train deep networks from a large database to establish robust semantic correspondence and accurate color mapping. In addition to semantic-based analysis, special target color transfer methods are proposed to satisfy specific requirements of certain application. Some color transfer methods with multi-parameters optimization are designed to adjust color scheme according to different parameter models such as RGB curves, saturation, white balance, contrast, etc. More complex lighting conditions are considered to produce natural color distribution for images. Other methods are designed for single-target optimization, including facial skin transfer, dehazing, etc.

Based on the previous survey [22], we propose an extended summary with new trends for image-based color transfer in this paper. Firstly, we introduce some fundamental theories about color transfer. Then, we discuss different technical routes. Finally, we compare different methods and explain the unsolved issues for the color transfer. The fundamental theories of color transfer have close relationship with multi-channel color representation, different color spaces, and parameter models. Such related elements construct basic functions to change color information in images while fitting some specific requirements. In following parts, we illustrate the details of fundamental and different kinds of color transfer methods. In Fig. 2, we show the taxonomy of color transfer methods for images. The contributions of our paper are summarized as:

- We sort out the background theories and mainstream technical routes of color transfer in the past 20 years. Basically, the paper provides an effective index for color transfer researching and learning.

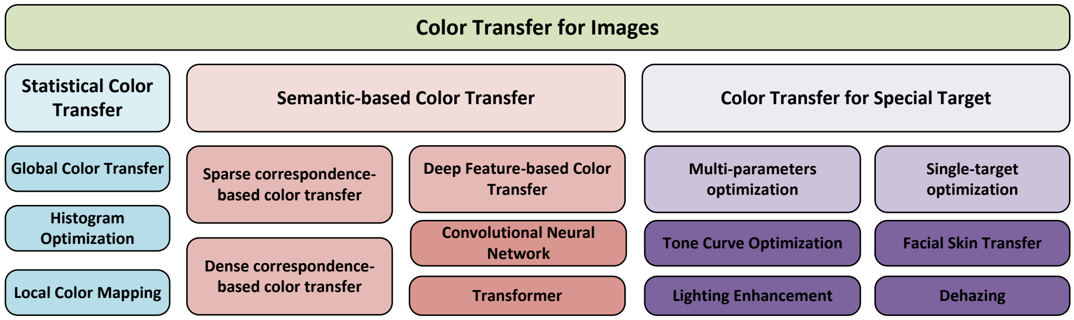

Fig. 2. A taxonomy of color transfer methods for images. The mainstream works can be classified into three categories: statistical color transfer; semantic-based color transfer; color transfer for special target.

- Following the previous survey [22], we introduce the new trends of color transfer, including deep feature-based frameworks, multi-parameters optimization, and color transfer for single target. Our works effectively improves the theoretical introduction of color transfer.
- For mainstream technical routes, we show more results in different color transfer tasks to illustrate related characteristics. Such characteristics are visualized intuitively. It is helpful for understanding the difference in performance between various methods.
- We discuss some unresolved issues of color transfer and propose potential solutions according to the exploration of existing technologies. It promotes the development of related research works in future.

2 COLOR REPRESENTATION AND EDITING

The color transfer is to improve the quality of color scheme or transfer specified color style for the source image according to the reference one. At the same time, the semantic information should not be changed. In order to achieve the goal, the measurable and accurate color representation with related editing tools should be established, which support more specific optimization tasks for color transfer. The cornerstone of modern digital imaging technology is RGB-based color system. Most digital imaging devices represent different colors based on the system. Almost all exist colors can be constructed by the three primary color channels. Intuitively, the color transfer can be implemented by optimizing the channels. However, the RGB values in an image are coupling and mutual influence. For instance, if a pixel of an image is located in a highlight area, its RGB values are higher than other places with higher probability. Independent optimization for RGB channels may break the original semantic information. To avoid the negative case, the global optimization of RGB channels is proposed to keep the semantic consistency of color distribution. However, the optimization reduces the flexibility and precision of color transfer. To establish more functional color representation, the Lab color space [91] is designed to solve the problem.

The Lab color space is constructed based on the sensitivity of human cone. It represents different colors with decoupled form. Color mapping from RGB to Lab can be regarded as an orthogonal transformation for color representation. The brightness and decoupled colors are represented in different channels. Benefited from the property, different channels of Lab can be adjusted independently. Considering that some related studies use different color spaces to implement color transfer, Reinhard *et al*. [89] presented a concluding article to estimate influences of different color spaces. The conclusion is that the decoupled color space has better performance in color transfer tasks.

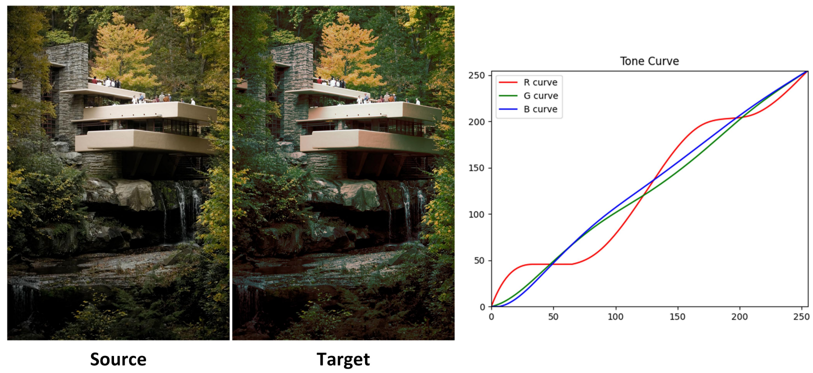

Fig. 3. Color adjustment by tone curve control. According to the manual adjustment, the color distributions of source image are changed to the target one. It is clear that the hue of the source image becomes warmer.

Based on the color representation, parameter models are discussed as the color editing tools. Such models are used to create natural and artistic images that meets aesthetic requirements with proper control. The most widely used models are RGB-based tone curve. The curve can be regarded as functions with statistical significance. With an ingenious design, colors of images can be strengthen or weaken based on specified requirement. An instance is shown in Fig. 3. According to the RGB imaging principle, each primary color has a complementary color achieved from the other two primary colors. The related tone curve reveals the relative strength between the primary color and its complementary one. Combining different adjustments for tone curve, some complex and accurate characteristics such as temperature, hue, exposure, contrast, and saturation can be optimized. As mentioned in Section 2, the Lab color space provides a decoupled form for color representation. According to the same theory of RGB-based tone curve, Lab-based tone curve can adjust color distribution with more flexibility. It has been successfully used in exposure adjustment.

The color transfer task is implemented based on the aforementioned color representation and related tools. For various transfer frameworks, the core difference is that how to use the tools to establish the color transfer while satisfying some specific requirements such as semantic consistency, lighting enhancement, reasonable contrast, etc. It can be summed up as two core tasks: semantic correspondence and global coordination. For the first one, it means that if there have semantic correspondence regions between source and reference images, the color distribution should be consistent between the regions. It satisfies the basic semantic consistency requirement. For the second one, the global parameters in image should be learned and extracted to guide the color transfer, which keeps the global coordination. For instance, the light intensity should be adjusted for the source image based on the reference one. The global parameters can be represented in a specific color space or some parametric models that are mentioned before. Based on the fundamental knowledge, we discuss different color transfer methods and related implementations.

3 STATISTICAL COLOR TRANSFER

For color transfer, the pioneer work [88] was proposed by Reinhard in 2001. It presented the basic model of transform function to match one kind of color distribution to another one. The color mapping is implemented in the Lab color space. The Lab color space is constructed based on the sensitivity of human cone. It represents different colors with decoupled form. Color mapping from RGB to Lab can be regarded as an orthogonal transformation

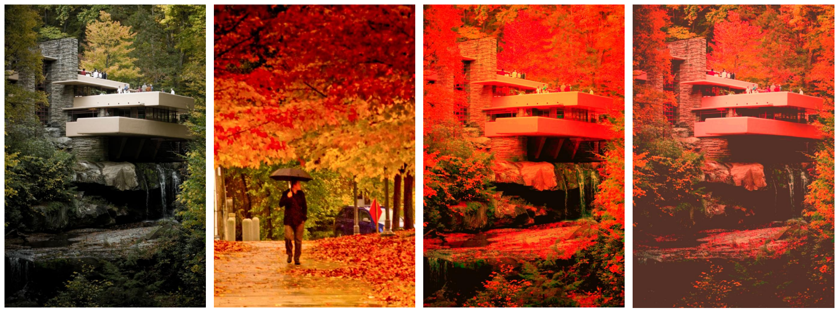

Fig. 4. An instance of color transfer by global strategy. Target A: The result by [88], the color over-flow is obvious ; B: The result by [88] with a degree control according to [108], some details are lost.

for color expression. The transfer is processed by

$$\begin{bmatrix} L \\ M \\ S \end{bmatrix} = \begin{bmatrix} 0.3811 & 0.5783 & 0.0402 \\ 0.1967 & 0.7244 & 0.0782 \\ 0.0241 & 0.1288 & 0.8444 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}, \tag{1}$$

$$\begin{bmatrix} l \\ a \\ b \end{bmatrix} = \begin{bmatrix} \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{3}} \\ \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{3}} & \frac{-2}{\sqrt{3}} \\ \frac{1}{\sqrt{3}} & \frac{-1}{\sqrt{3}} & 0 \end{bmatrix} \begin{bmatrix} \log L \\ \log M \\ \log S \end{bmatrix}, \tag{2}$$

where the RGB values can be transferred into lab values in Lab color space. The brightness and decoupled colors are represented in different channels. Benefited from the property, different channels of Lab can be adjusted independently. The color transfer is implemented by standard deviation-based alignment, $l^{'} = \sigma_t^l/\sigma_s^l * (l - \bar{l})$, where $l^{'}$ is the transferred l value, σ_s^l and σ_t^l are standard deviations of L-channel of source and reference images, $\bar{l}$ means the average value of L-channel. Other channels are processed with the same computation. After the color transfer, the generated color distributions are aligned according to the reference image. The main drawback of the method is that it produces unnatural colors when the source image and the reference one have significantly different color distributions. For this issue, some urgent works are proposed to establish more accurate color transformation, which can be roughly divided into three categories: improved global color transfer, histogram optimization, and local color mapping with sub-division alignment.

3.1 Global Color Transfer

The basic idea of improved global color transfer is to adjust color mapping strategy to generate more reasonable color scheme. Toet provided a color mapping solution [106] for night-time imagery. The improvement is that it designs a pyramid gray-level fusion scheme to correct the luminance represented by L-channel in Lab color space. The generated L-channel information are used to replace the original luminance that restores the color contrast. It can be regarded as a successful application of Lab-based color transfer. The correction process can be formulated as

$$G_l(i, j) = \sum_{m,n \in [-2,2]} w(m, n) G_{l-1}(2i + m, 2j + n), \tag{3}$$

where w represents a standard binomial Gaussian filter of 5×5 pixels extent, G_l means the related level of Gaussian pyramid. The formulation constructs relationships between each pixel to its neighbors which is useful to

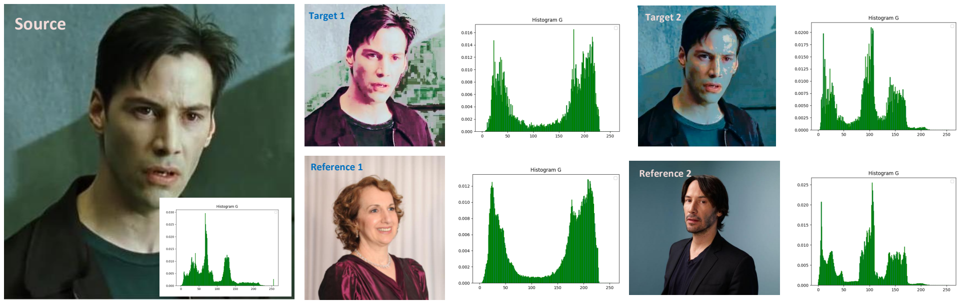

Fig. 5. Some instances of color transfer by histogram optimization.

optimize luminance contrast. Wang *et al*. [108] introduced a movie clip approach for image-based color transfer, which generates mapping sequence by B-spline curves. It provides a degree control for Reinhard's method to avoid color overflow. Kumar *et al*. [49] provided a color transfer method in YCbCr color space with optical flow optimization. It has better performance for action sequence pictures in compression and color transfer tasks. Lee *et al*. [51] utilized the Lab-based color transfer to reduce the loss of color information during the secure image transmission. Basically, the mentioned methods are implemented based on the strict global color transfer strategy that reduces flexibility.

Some methods attempt to design the adaptive color transfer scheme to fit different color distributions. Yin *et al*. designed a neural network-based method [127] to address the influence of different camera devices with complex lighting conditions. It is an early approach to utilize learning framework in color transfer. The improvement of the method is that a non-linear model implemented by the neural network [48] is used to guide the color transfer. Comparing to the linear mapping, the proposed model generates more accurate result with the minimum loss between estimated colors and related ground truth. It can be regarded as a feasible color correction. Pitie *et al*. [83] implemented the color transfer based on a N-Dimensional Probability Density Function (N-D PDF). The PDF is used to describe different color distributions in the color mapping. Based on the similar consideration, Su *et al*. [99] presented a probabilistic control model to provide corruptive artifacts suppression in color transfer. In summary, the advantage of such methods is that they generate new color scheme with global color consistency. However, it cannot establish fine-grained local color mapping between the source and reference images. The drawback causes unnatural colors or unbalance color distribution into the target image, as shown in Fig. 4.

3.2 Histogram Optimization

To balance local color mapping and global consistency, histogram optimization and related frameworks are proposed. The histogram optimization (specification) establishes the band-based representation of different colors and utilizes optimization strategies to match color distributions. It can be represented as

$$I_{target} = T(I_{source}), \tag{4}$$

where I_{target} represents the target image (color transfer result) from the source image I_{source} after histogram optimization. The histogram optimization T is to minimize the metric of band-based representations between I_{source} and $I_{reference}$. According to the descriptions of [27], T should consider dynamic range and contrast while avoiding color distortions or artifacts. An implementation is provided as

$$T(x) = b_{k-1} + \frac{r_k t^2 + d_{k-1}(1-t)t}{r_k + (d_k + d_{k-1} - 2r_k)(1-t)t}(b_k - b_{k-1}), \tag{5}$$

where $b_k = T(a_k)$ is the transferred key color, $d_k = T(a_k)'$ means the contrast adjustment, $r_k = (b_k - b_{k-1})/(a_k - a_{k-1})$, $t = (x - a_{k-1})/(a_k - a_{k-1})$, $x \in [a_{k-1}, a_k]$.The key colors (or palette) are selected to represent the peak values of color distributions which are used to construct benchmark mapping for T. Based on the key color mapping, other intermediate colors can be edited. Different kinds of strategies are proposed to balance the mentioned targets.

Morovic *et al*. [74] proposed a 3D color histogram matching method for color transfer. It utilizes the Earth Mover's distance metric to transfer the histogram between images. Grundland *et al*. [27] used histogram warping to adjust the source color distribution to fit the reference one with any desired degree of accuracy. Neumann *et al*. [75] used a permissive, or optionally strict 3D histogram matching to transfer colors. It is similar to the sampling of multi-variable functions and applying a sequential chain of conditional probability density functions. Xiao *et al*. [115] proposed a gradient-preserving color transfer method which is implemented by histogram matching and a gradient-preserving optimization. It achieves more natural and fidelity results. Pouli *et al*. [85] presented a novel histogram reshaping technique in CIELab color space, which provides more controllable flexibility in the color transfer. He improved the framework with arbitrary dynamic range control [86]. Papadakis *et al*. [81] designed a variational formulation to match histogram for the color transfer. The formulation includes three items: cumulative histograms balance, maintain colors and adjust geometry, which are used to generate more reasonable color scheme. In summary, such methods map colors between images based on the histogram analysis which means that more accurate statistical color distribution is considered. Although there have improvements over the global color transfer, these methods are still global strategies without local patch analysis. In Fig. 5, some related instances are shown.

3.3 Local Color Mapping

The histogram optimization also can be regarded as a kind of global color transfer. The subtle difference is that it considers the proportion of color distributions in color transfer. The performance of the method is affected by the closeness of the proportion. To achieve more accurate and flexible color transfer result, some methods establish local color mapping in images, which increases the degrees of freedom for color transfer or colorization. The color contrast in different areas can be enhanced with local color mapping strategies. The details are discussed in following parts.

Greenfield *et al*. [26] classified different colors into several regular ones to build a palette-based color association. Then, the color transfer can be processed by matching the associations between images. Comparing the variance normalization [88], the method implements more accurate alignment for different levels of colors. It has started to consider balancing the relationship between local and global color distributions. The palette-based color transfer also introduced in some other methods [84, 132, 139]. Based on the mentioned ND-PDF [83], Pitie *et al*. [84] improved the framework that preserves the original gradient field in transfer result. It aligns the palette-based colors between images to implement local color mapping while keeping second-order continuity as much as possible. Zhang *et al*. [132] proposed a blind color separation model for palette-based color transfer. The separation model considers different prior knowledge, including sparsity [133], smoothness [13], and unity. Sparsity means that the palette colors should highlight the saliency region and the color mapping should reduce the color-based difference in related palette bin. For the mentioned prior knowledge, the separation model provides mathematical formulations with related optimization tools [117].

Some local color mapping methods attempt to align different colors based on eigenvector-based analysis or Expectation-Maximization. Xiao *et al*. [114] proposed a color transfer framework that considers color distributions and related segmentations at the same time. For color distribution, the framework utilizes the SVD algorithm [46] to decompose the covariance matrices of RGB values. Then, the color distributions represented by the shape of RGB values in the feature space can be aligned with a set of shape-preserving transformations. Finally, two color

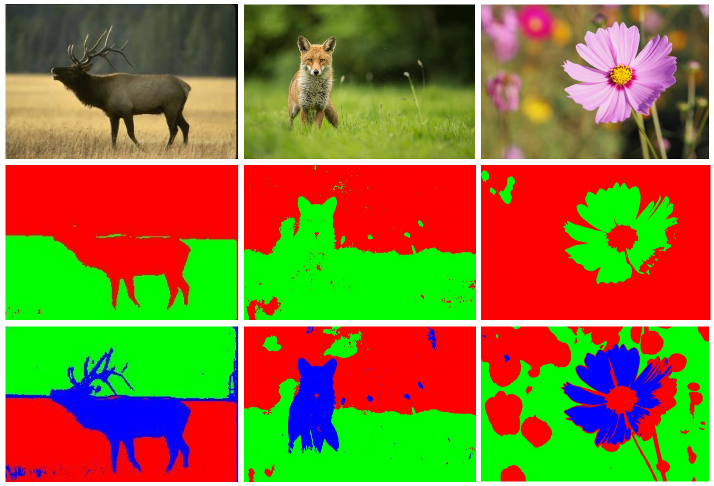

Fig. 6. An instance of GMM-based image segmentation. First row: input images; second row: segmentation results with two classes; third row: segmentation result with three classes.

distributions extracted from the source and target images can be registered based on the swatch-pairs. Abadpour *et al*. [1] provided a principal component analysis (PCA)-based framework for color transfer task. The PCA is used to reduce the dimension of color space to extract main color classes. Then, different colors can be aligned between source and reference images. Tai *et al*. [100] utilized the Expectation-Maximization scheme [10] to impose both spatial and color smoothness to infer natural connectivity among pixels. Different optimal regions are computed by Gaussian Mixture Model (GMM). The classification probability of a pixel can be estimated by

$$iP_{xy} = \frac{exp(-(I(x,y)-\mu_i)^2/2\sigma_i^2)}{\sum_{j=1}^{N} exp(-(I(x,y)-\mu_j)^2/2\sigma_j^2)}, \tag{6}$$

where $I(x,y)$ takes the RGB values of a pixel, which belongs to the ith classification according to the Gaussian distribution $G_i(i;\mu_i,\sigma_i)$, $\mu_i = \sum_{x,y} iP_{xy}I(x,y)/Z, \sigma_i = \sqrt{\sum_{x,y} iP_{xy}(I(x,y)-\mu_i)^2/Z}, Z = \sum_{x,y} iP_{xy}$. Based on an iteration scheme for Equation 6, the GMM-based segmentation can be achieved. With the GMM-based segmentation, the local color mapping can be processed that is according to the order of luminance channels. In Fig. 6, some instances of GMM-based segmentation results are shown. Following the proposed structure, some researcher designed related variant methods [28, 101] to improve the performance for images with overlapped and transparent areas.

Basically, such methods still do not consider the specific semantic information for color transfer. They can not transfer colors between significant semantic-association regions. Especially, when these regions do not conform to the correspondence based on the color-based probability distribution, some unnatural color transfer results may be produced. Therefore, some researchers attempt to introduce semantic analysis to improve the accuracy of color transfer.

4 SEMANTIC-BASED COLOR TRANSFER

As mentioned in Section 3, the statistical color transfer methods map colors based on global or local color distributions. Such methods do not consider the semantic correspondence which affects the accuracy and

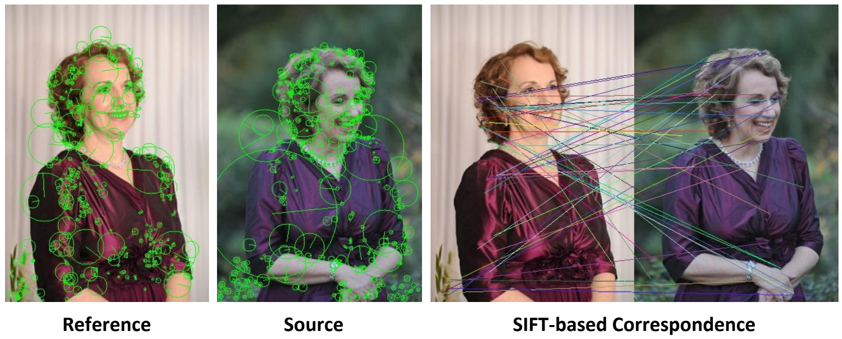

Fig. 7. An instance of SIFT-based semantic correspondence.

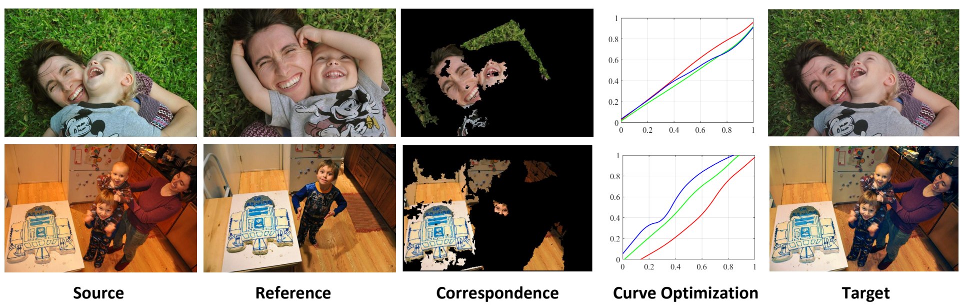

Fig. 8. Two instances of dense correspondence-based color transfer.

semantic continuity in color transfer. Therefore, the semantic-based color transfer methods are proposed to solve the problem. According to the selection of semantic feature, the methods can be classified into three groups: sparse, dense, and deep feature correspondence.

4.1 Sparse Correspondence

The sparse correspondence-based methods detect association between images based on sparse features, including scale space [63], speeded up robust features (SURF) [8], color moments[105], shape index [9], Random sample consensus (RANSAC) [23, 79], scale invariant feature transform (SIFT) [69], etc. In Fig. 7, we show an instance of SIFT-based correspondence [69]. As a representative feature, SIFT is suitable to establish sparse semantic correspondences for color transfer and correction. Yamamoto *et al.* [121] proposed a multi-view system for color correction based on SIFT. He also extended the method for video color correction [120]. Tehrani *et al.* [104] modified SIFT method for color correction in multi-camera system. Faridul *et al.* [21] proposed a color mapping method based on SIFT semantic correspondence. Sheng *et al.* [94] presented a Gabor feature-based framework to establish color mapping for video colorization. It can be regarded as an earlier work that utilizes convolution-like semantic analysis in color transfer. Park *et al.* [82] presented a robust low-rank matrix factorization method to estimate the control parameters for color transfer. The advantage of the method is that the sparse correspondence can be detected conveniently. The detection is robust to the discontinuous semantic regions. However, such methods can not estimate accurate global color mapping for continuous semantic regions. The drawback takes some errors for estimations of illumination, saturation, and contrast.

4.2 Dense Correspondence

To estimate accurate color mapping for continuous semantic regions, the dense correspondence-based methods are proposed. Comparing to the sparse correspondence frameworks, such methods attempt to detect the continuous semantic regions in images to generate color scheme. The features used for region detection include rank transform (RT) [14], texture analysis [32, 97], mean shift [16], color histogram [43, 59], regional foremost matching [93], Gaussian clusters [37], saliency region [113], patchmatch [6, 140], etc. As one of the most representative feature, patchmatch has been used in many works. Barnes *et al*. [7] refined the patchmatch-based framework to make it more practical. HaCohen *et al*. [30] presented a patchmatch-based method to detect non-rigid dense correspondence in images. The method connects semantic areas between source and reference images which take consistent tone information into the target one. The basic contribution of the method is to provide a consistency estimation between patches, which can be formulated as

$$C\left(u,v\right)=\frac{\|T^{v}(v_c)-T^{v}(v_c)\|_2}{\|T^{u}(u_c)-T^{u}(v_c)\|_2}, \tag{7}$$

where u_c and v_c are two patches from source image, u and v are centers of u and v, T^u and T^v are two patches from reference image which corresponds to u and v with transformation T. The consistency estimation $C(u,v)$ evaluate the similarity between patches while considers the adjacent regions. To extend the corresponding regions between source and reference images, the patch searching scheme is proposed as

$$C\left(Z\right)=\frac{\left|\{(u,v)\in J(Z)\ s.t.\ C(u,v)>\tau_{global}\}\right|}{|J(Z)|}, \tag{8}$$

where Z is a region that contains pairs u and v, $J(Z)$ is a random subset of Z. The scheme is to account the patch pairs that satisfy the threshold condition $C(u,v)>\tau_{global}$. The advantage is that larger regions can be searched and connected, which can establish the non-rigid region correspondence. In Fig. 8, we show some instances by [30]. With the similar idea, Shih *et al*. [95] introduced the patchmatch into a data-driven photo composition system. HaCohen *et al*. [31] extended the framework and constructed a patchmatch-graph to share content of a set of photos for color transfer.

Niu *et al*. [77] proposed an image quality assessment to measure the qulity of color correction. The SIFT flow is used to achieve regional registration between the two input images and generate a matching image. He extended the framework [78] for color correction of stereoscopic images and videos. Panetta *et al*. [80] proposed a selective color transfer based on Hue-Division-Based color region segmentation. It can transfer color distributions from one object to another while keeping the global color consistency. Lew *et al*. [53] provided a survey for content-based multimedia information retrieval. It discusses different issues in semantic correspondence task, including concept detection in complex backgrounds, semantic-based similarity measurement, and different color spaces. The advantages of dense correspondence-based methods include better semantic consistent, global lighting optimization, and more natural color distribution. However, the dense correspondence is difficult to be detected. The related methods are sensitive to pose variant and zoom of semantic regions. Once the detection fails to correspond the continuous semantic regions between images, the performance of color transfer must be reduced.

4.3 Deep Feature

Following the development of deep learning framework [47], many researchers use related technologies to implement color transfer. Deep features learned from the framework can be used to represent accurate semantic information. Liao *et al*. [60] utilized the property to successfully build the deep feature-based semantic correspondence between images. An visualization instance is shown in Fig. [92]. For color transfer, deep feature-based

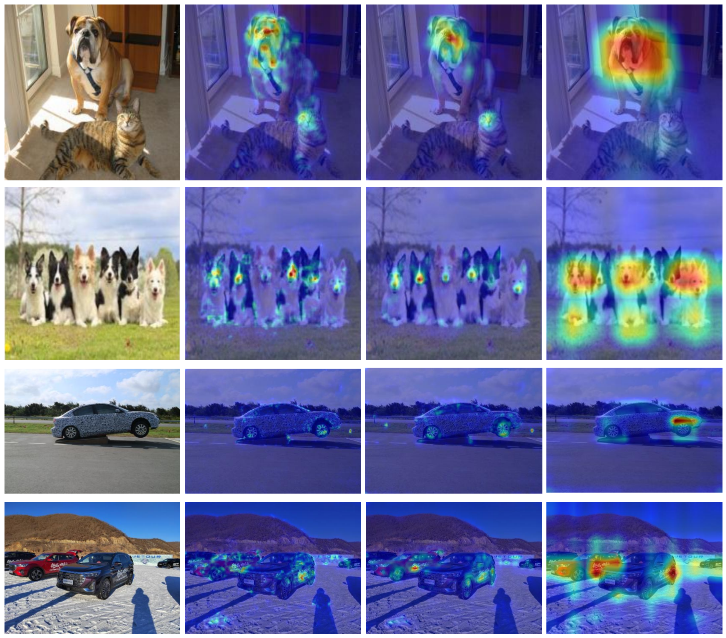

Fig. 9. Color maps for deep feature visualization [92] based on VGG19.

frameworks consider background [25], photorealism regularization [52], semantic entanglement [98], and semantic segmentation [5, 12] to design the loss function. Following the research works, Ming *et al*. [34] presented a color transfer framework based on the deep feature. The framework is constructed by two parts: similarity sub-net and colorization sub-net. The similarity sub-net is to detect the semantic correspondence based on the deep features. It utilizes the low-frequency corresponding represented by different levels of CNN to establish the robust semantic correspondence, which are represented as

$$sim^i_{T\to R}(p) = d(F^i_T(p), F^i_R(\phi_{T\to R}(p))), sim^i_{R\to T}(p) = d(F^i_T(\phi_{R\to T}((\phi_{T\to R}(p))), F^i_R(\phi_{T\to R}(p))), \tag{9}$$

where $sim_{T\to R}$ and $sim_{R\to T}$ are bidirectional similarity maps of two images T and R. The similarity sub-net feeds two luminance channels T_L and R_L into the VGG-19 and outputs five-level feature map pyramids $\{F^i_{T_L}(p)\}_{i=1,...,5}$ and $\{F^i_{R_L}(p)\}_{i=1,...,5}$ respectively. Then, the bidirectional similarity maps are computed between F^i_T and F^i_R at each pixel p. The colorization sub-net is to generate new color distribution for source image according to the reference one, the related loss function is formulated as

$$\theta^* = \underset{\theta}{argmin}(L_{chrom}(P^T_{ab}) + \alpha L_{perc}(P_{ab})), \tag{10}$$

where θ represent the parameter set for network, P_{ab} and P^T_{ab} are colorized with the guidance of $R^{'}_{ab}$(color channels of reference image with aligned pixels), T_L, and $T^{'}_{ab}$(color channels of source image with aligned pixels). With the colorization sub-net, new color distributions are generated for source image according to the reference one. In Fig. 10, two instances of deep feature-based color transfer method [34] are shown. The authors further improved the framework [35] with dense semantic correspondence to achieve spatially variant and globally coherent in color transfer.

Fig. 10. Color transfer results by deep feature-based framework [34].

Zhang *et al*. [131] and Meyer *et al*. [72] extended the same framework into video-based color transfer. Lee *et al*. [50] combined the deep feature analysis and histogram optimization in color transfer. Zhao *et al*. [138] proposed a saliency map-guided colorization based on a generative adversarial network. It avoids the semantic confusion and color bleeding in the final colorized image. Jiang *et al*. [42] utilized the transformer to extract deep features for color transfer. It achieves better result than CNN-based frameworks. Ho *et al*. [36] proposed a color style transfer framework based on well-designed deep neural network. Virtusio *et al*. [107] presented a CNN-based framework for palette color transfer between images. Hu *et al*. [39] introduced a method to extract color-concept associations automatically from a set of concept images. The framework employed the similar color mapping introduced in [34].

The most significant advantage of deep feature-based frameworks is that they recognize accurate semantic information between images to build the correspondence. Comparing to the traditional semantic-based methods, the deep feature-based frameworks are robust to different poses and non-rigid transfer [34]. It can implement lossless separation of color channels by encoding-decoding structure [19]. The robustness benefits from the analysis for low-frequency information by the deep neural network. Even the images have not correspondence based on patchmatch in RGB-level, the framework can still recognize semantic correspondence in lower layer of the network. However, the deep feature-based frameworks ignore complex influences of lighting which produce unnatural colors in target image. The boundaries of semantic correspondence and non-correspondence regions are broken during the color transfer. Therefore, some researchers attempt to propose special target color transfer rather than general framework.

5 COLOR TRANSFER FOR SPECIAL TARGET

Some color transfer methods are designed for special targets, including contrast optimization, exposure correction, portrait enhancement, dehazing, etc. According to the different targets, such methods can be divided into two

Fig. 11. Some instances of multi-parameters optimization for low-light image color correction. Zero-DCE: [29]; RUAS: [66]

categories: multi-parameters optimization and single-target optimization. In following parts, we introduce the details.

5.1 Multi-parameters Optimization

The multi-parameters optimization attempts to adjust lighting model to improve the quality of color distribution. It is implemented by the adjustment of multi-parameters and used to optimize illumination that can be regarded as a special kind of color transfer task. The reference images are selected from image dataset with correct exposure to train the lighting model. The parameters that used to represent the lighting model have relationships with high dynamic range imaging [40, 90, 130], multi-scale function [119], light enhancement curve (LE-curve) [29], extreme channels [24, 137], attention map [70, 118], illumination [71, 135], harmonic color model [122], color-gray-difference (CGD) space [123], and Retinex-inspired model [66, 112]. To enhance the color scheme, such methods optimize the related models to reconstruct local color contrast while keeping the global color distribution. Especially for pictures with abnormal exposure, the methods can improve the quality with detail recovery. Some instances are shown in Fig. 11. For some images with complex exposure conditions and large contrast differences, it is difficult to directly establish a unified lighting optimization model. Some multi-parameters optimization methods can be used as the pre-processing steps for more accurate frameworks. More commonly used methods are L-channel alignment [88] and HDR adjustment [90]. In [70], some sophisticated image quality estimations are employed for accurate lighting optimization, including darkness estimation and blur estimation. Naturally, semantic segmentation is an important pre-processing for semantic consistency lighting optimization [136].

Although the optimization can improve the quality of color distribution, there are still some limitations. Firstly, the lighting model used in the optimization is a global one in most cases, which means that the adjustment can not provide dynamic lighting analysis in different regions of the source image. Some subtle differences between different regions are ignored that reduce the accuracy of color transfer or enhancement. Even some works attempt to balance contrast by high dynamic range imaging in different regions to enhance the quality of color distribution, the saliency objects can not be processed independently that limits the flexibility. Secondly, the semantic information are not considered adequately, including some common background regions like sky, grass, sea, etc. The drawback reduces the naturalness of the picture. Finally, there have no high quality research works to combine prior knowledge of color transfer into lighting optimization. In most cases, the two tasks are implemented independently. Even the deep feature-based methods bring a significant performance boost for color transfer, it is still difficult to establish a general framework to solve the above problems. Therefore, some research works turn to build designated framework for single-target optimization.

5.2 Single-target Optimization

Single-target optimization frameworks focus on specific color transfer task rather than global lighting enhancement or contrast optimization. Such frameworks can generate accurate color schemes with the balance between semantic-based color transfer and specified requirements. Some of them attempt to implement accurate color mapping between portrait photos. Li *et al*. [55] proposed a facial region-based color transfer method to implement the color correction for portrait photo fusion. Liu *et al*. [65] proposed a fully automatic system for facial make-up transfer with style synthesis. The system utilizes a multiple tree-structured super-graphs model to implement multi-level facial attribute analysis. Yang *et al*. [124] presented a color transfer method for portraits by exploring their high-level semantic information. Li *et al*. [56] addressed the facial makeup transfer by incorporating both global domain-level loss and local instance-level loss in an dual input/output Generative Adversarial Network (GAN). Thao *et al*. [76] proposed a facial pattern transfer framework that can transfer different kinds of makeups, including stickers, blushes, and jewelries. Liu *et al*. [67] proposed a facial-expression-aware emotional color transfer framework that considers high-level visual facial features to generate more accurate color scheme.

Some frameworks attempt to remove specific environmental impact in color transfer. Li *et al*. [54] proposed a weakly supervised color transfer method to correct color distortion in underwater images. Jiang *et al*. [41] presented an image dehazing method to consider of the illumination characteristics for color transfer. Son *et al*. [96] proposed a color regulation framework that utilizes the near-infrared imaging to fix color distortion produced by haze. Ancuti *et al*. [4] introduced a color channel transfer method to substantially improve the performance of various dehazing techniques. Yin *et al*. [128] developed a variational image dehazing method based on a dehazing model that restores image fidelity, brightness, and sharpness effectively. Rajput *et al*. [87] designed a nighttime haze removal method that automatically selects reference image to implement color transfer for the target. Christen *et al*. [15] extended the transport-based neural style transfer approach to obtain a complete pipeline for transferring color information onto smoke simulations. Ye *et al*. [126] proposed a style adaptation network to implement color correction for underwater images. The method transfers color distributions from normal images to the underwater ones without underwater image set. Gilberto *et al*. [3] introduced a local color transfer methodology for shadow removal. The method divides lighting signals from CIELab color space. Based on the processing, pixels in shaded areas are restored. Yang *et al*. [110] proposed a convolutional neural network (CNN)-based framework to learn hierarchical statistical features related to color cast and contrast degradation. It is used to correct color information for underwater images. Obviously, the mentioned methods can just used in certain color transfer task that limits the scope of application.

In summary, the mainstream technical routes and related implementations are introduced in previous sections. According to the exploration for the methods, it can be known that they have different characteristics in color transfer tasks, including sensitivity for semantic regions, consistency of global color distribution, adaptability for complex lighting conditions, and specificity for special target. Some representative methods with characters are

Table 1. Overview of some representative methods with related characteristics.

Methods	Classification	Color Space	Semantic Analysis	Parameter Model	Lighting Optimization	Deep Feature	Scope
Reinhard *et al.* [88]	Statistical color transfer	Lab	——	——	L-channel normalization	——	Generic
Alexander [106]	Statistical color transfer	Lab	——	Pyramidal image fusion	Luminance Contrast	——	Generic
Xiao *et al.* [49]	Statistical color transfer	RGB	Swatch pairs	Swatches' statistics	Swatch-based correction	——	Generic
Grundland *et al.* [27]	Statistical color transfer	RGB	——	RGB-based histogram	Histogram warpping	——	Generic
Pouli *et al.* [85]	Statistical color transfer	CIELab	Color palette	Tone reproduction	High dynamic range	——	Generic
Tai *et al.* [100]	Statistical color transfer	RGB	Segmentation	——	——	——	Generic
Kumar *et al.* [49]	Statistical color transfer	YCbCr	Pixel group	Chrominance	Optical flow	——	Motion estimation
Pitie *et al.* [83]	Statistical color transfer	RGB	Pixel group	——	——	——	Generic
Faridul *et al.* [21]	Semantic-based	RGB	SIFT	Channel-wise	Cross-channel	——	Generic
Park *et al.* [82]	Semantic-based	RGB	SIFT	Global parameter	Global parameter	——	Generic
HaCohen *et al.* [30]	Semantic-based	RGB	Patchmatch	Tone curve	Tone curve	——	Generic
Xia [113]	Semantic-based	CIELab	Saliency map	——	——	——	Generic
Ming *et al.*(a) [34]	Semantic-based	RGB	Patchmatch in CNN	——	——	CNN-based	Generic
Ming *et al.*(b) [35]	Semantic-based	RGB	Nearest-neighbor field in CNN	——	——	CNN-based	Generic
Lee *et al.* [50]	Semantic-based	Lab	Segment-wise	Histogram analogy	Histogram analogy	CNN-based	Generic
Jiang *et al.* [42]	Semantic-based	RGB	Functional correspondence	Functional map	Functional map	Attention	Generic
Guo *et al.* [29]	Special Target	RGB	——	Light curve	Light curve	CNN-based	Low lighting
Liu *et al.*(a) [66]	Special Target	RGB	——	Retinex-inspired model	Illumination module	CNN-based	Low lighting
Thao *et al.* [76]	Special Target	RGB	Texture matching	Color transfer branch	Color transfer branch	GAN-based	Facial image
Liu *et al.*(b) [67]	Special Target	RGB	——	Emotion model	Emotion model	CNN-based	Facial image
Li *et al.* [54]	Special Target	RGB	——	——	——	GAN-based	Underwater Image
Yin *et al.* [128]	Special Target	RGB	——	Texture refinement	——	CNN-based	Dehazing

compared in Table 1. In following parts, we provide comparisons of some representative methods for further understanding.

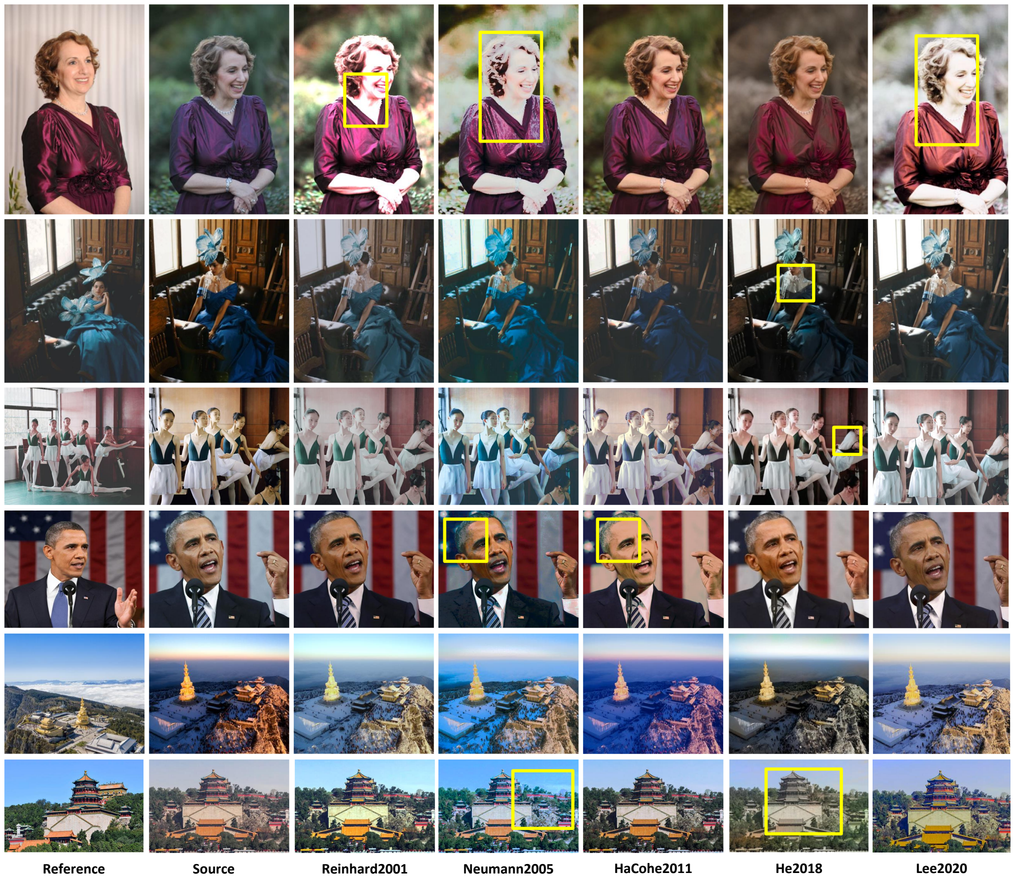

Fig. 12. Comparisons of color transfer methods for images with close semantic correspondence. Some undesired regions with abnormal exposure and color degradation are labeled by yellow boxes. Methods: Reinhard2001 [88]; Neumann2005 [75]; HaCohen2011 [30]; He2018 [34]; Lee2020[50].

6 COMPARISONS

In this part, we compare different color transfer methods in different tasks to show the related characteristics. According to the different conditions in the color transfer tasks, it can be divided into three groups to build estimations, including color transfer for images with close semantic correspondence, sparse semantic correspondence, and low lighting condition. For quantitative analysis, we measure some representative methods according to several mainstream image quality assessments.

6.1 Close Semantic Correspondence

Color transfer for images with close semantic correspondence should build new color scheme for the target image with semantically consistent. The quality of the transfer method is based on the performance of semantic detection and related color mapping strategy. We compare the color transfer results by different methods for the task. Some instances are shown in Fig. 12. As the pioneer work, Lab color space-based color transfer [88]

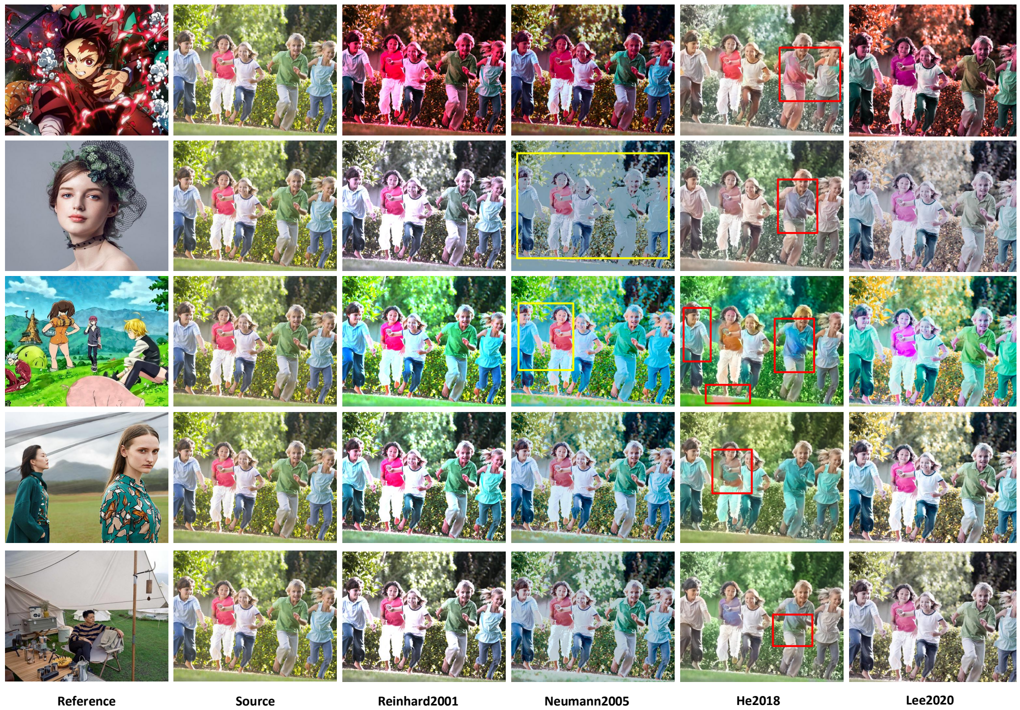

Fig. 13. Comparisons of color transfer methods for images with sparse semantic correspondence (same source image and difference reference ones). Some regions with abnormal exposure are labeled by yellow boxes; some regions with discontinuous color distribution are labeled by red boxes. Methods: Reinhard2001 [88]; Neumann2005 [75]; He2018 [34]; Lee2020[50].

can generate global color mapping between images. However, the semantically consistent can not be kept. For the first instance in Fig. 12, the method generates overexposed picture. Histogram matching [75] has the worst performance for new color generation. The reason is that the method mandatory establishes the best histogram matching which produces more unnatural color distributions.

Once the semantic correspondence can be detected, the dense correspondence-based color transfer [30] achieves more accurate results. But the robustness of the detection is not stable. For the fifth instance, the method generates unnatural color distribution even there have obvious semantic correspondence regions. Lighting changes produced in complex weather conditions and different gestures of the golden Buddha reduce the performance for the color transfer. The deep feature-based methods [34, 50] utilize robust semantic detection in low frequency level to generate new color scheme. To a certain extent, the methods solve the shortcomings of traditional methods on semantic correspondence detection. However, such methods depend on the training dataset. Once the semantic regions between images are not covered in the dataset, the performance is reduced obviously. In Fig. 12, the last instance by [34] and first instance by [50] show the mentioned instability. We label the undesired regions in color transfer with yellow boxes.

6.2 Sparse Semantic Correspondence

Color transfer methods can generate reasonable color scheme between images with close semantic correspondence that controls color distributions between images. For images without close semantic correspondence, the

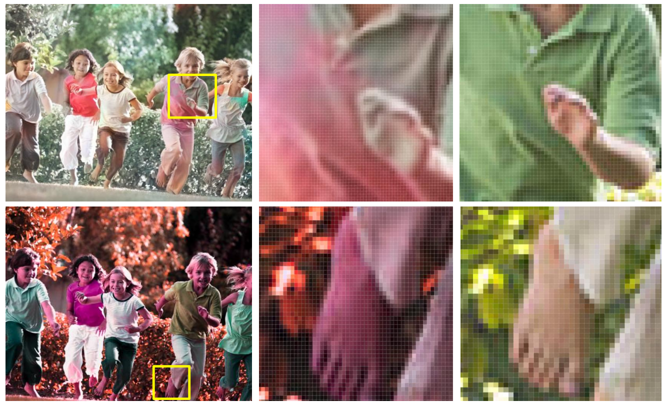

Fig. 14. Two failed instances of color transfer. First row: color transfer result by He2018 [34], the continuity of the color distribution is broken; second row: color transfer result by Lee2020[50], the color deviation is produced which breaks the naturalness of the image.

performance of the methods will be significantly challenged. To evaluate the robustness and applicability in such condition, we use one source image with different reference ones to build color transfer results by different methods. Some instances are shown in Fig. 13. Due to the sparse semantic correspondence between images, the performance of histogram matching-based method [75] are further reduced even with the correction by the deep feature [50]. For the second instance in Fig. 13, the tone information of the images are completely destroyed. Dense correspondence-based methods are complete failure cause there have no close semantic correspondence can be detected. Lab color space-based color transfer [88] totally lost natural color mapping in target images. Balances between global and local color distributions are broken by [34]. In Fig. 14, we show these failed cases individually. In general, color transfer for images with sparse semantic correspondence is still a challenging task. As a similar research field, style transfer methods propose solutions to transfer high-precision pixel details by corresponding distributions of low-frequency signals. In this way, the transfer of high-frequency image information or "style" can be realized without close semantic correspondence. In Fig. 15, we compare some deep feature-based color transfer and style transfer methods [57, 58, 129] in images with complex conditions. It is clear that the semantic objects are changed by style transfer, even the reference images are also real photos.

6.3 Low Lighting Condition

Another difficulty of color transfer is that the low lighting condition takes uncertain impact for new color scheme generation. In such condition, some parameters includes contrast, white balance and saturation are significantly affected. We evaluate the performance of different methods for images with low lighting condition. Some instances are shown in Fig. 16. It is clear that the color transfer methods [29, 66] with multi-parameters optimization can achieve better result. Such methods don't even require the specified reference images. The pre-training model has been constructed from the well-designed dataset. It provides the better reference choice automatically. However, the overexposure and underexposure cannot be completely avoided (regions labeled by red boxes in Fig. 16). For second and fourth instances by [66], the situations are exhibited. The deep exemplar-based method [34] can not improve the low lighting condition. The reason is that the method does not optimize global parameter model which controls the illumination. The Lab color space-based color transfer [88] fixes the light intensity in target

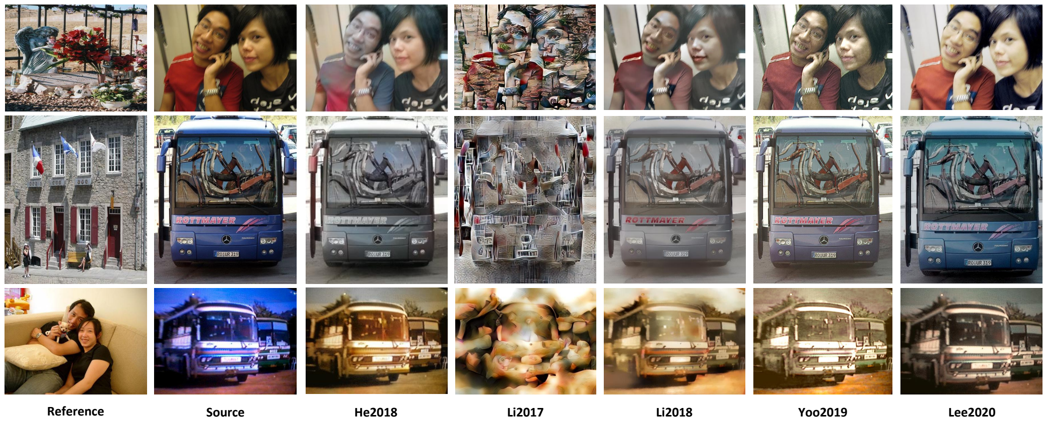

Fig. 15. Comparisons of color transfer methods for images with complex conditions(blur, reflection and old style). Methods: He2018 [34]; Li2017 [57]; Li2018 [58]; Yoo2019 [129]; Lee2020[50].

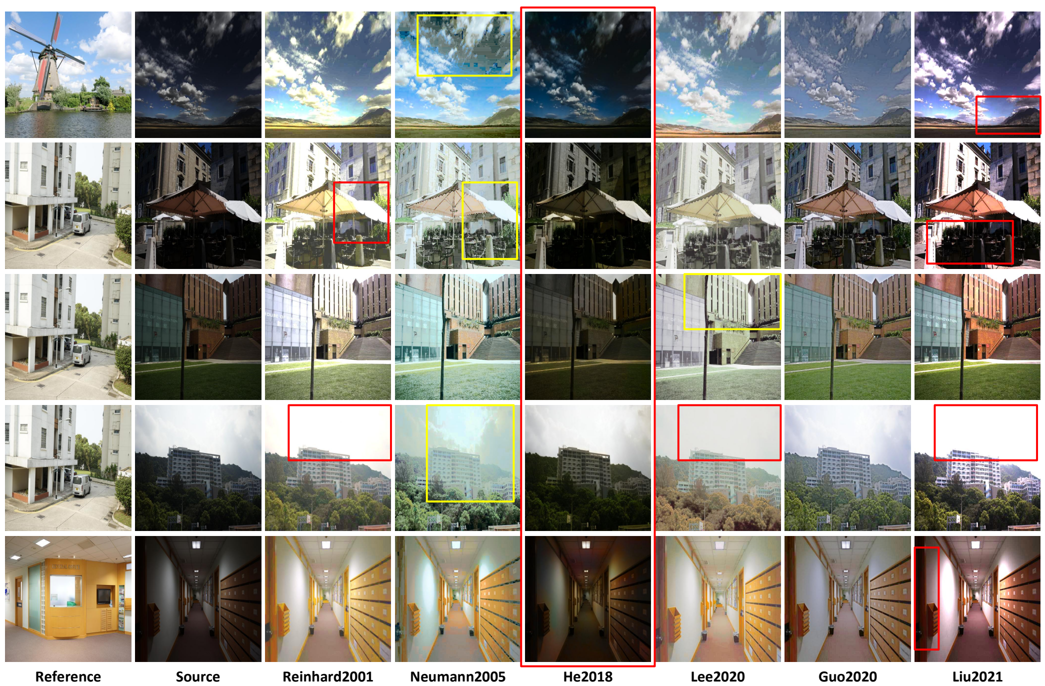

Fig. 16. Comparisons of color transfer methods for images with low lighting condition. Some undesired regions are labeled by yellow boxes; some regions with wrong exposure are labeled by red boxes. Methods: Reinhard2001 [88]; Neumann2005 [75]; He2018 [34]; Lee2020[50]; Guo2020 [29]; Liu2021 [66].

Table 2. Image quality assessments for images with close semantic correspondence.

	Brisque	ClipIQA+	CNNIQA	DBCNN	MUSIQ	NIMA
Reinhard *et al.* **[88]**	15.3744	0.6738	0.2013	57.2871	**68.1901**	4.7859
Neuman *et al.* **[75]**	14.9253	0.5923	**0.3537**	56.5235	64.0173	**4.8617**
HaCohe *et al.* **[30]**	16.9188	**0.6793**	-0.1665	**58.2248**	66.9544	4.8098
He *et al.* **[34]**	**27.6306**	0.6308	-1.5091	43.8515	62.3765	4.4417
Lee *et al.* **[50]**	15.5302	0.6681	-0.1819	56.3676	66.9298	4.8137

Table 3. Image quality assessments for images (COCO2017) with sparse semantic correspondence.

	Brisque	ClipIQA+	CNNIQA	DBCNN	MUSIQ	NIMA
Reinhard *et al.* **[88]**	20.8816	0.4829	**0.6879**	54.0763	68.5808	4.5861
Neuman *et al.* **[75]**	20.5048	0.4932	0.6831	**59.3659**	**69.3625**	**5.1257**
He *et al.* **[34]**	**29.8663**	0.4913	-1.5036	40.2923	64.1317	4.1233
Lee *et al.* **[50]**	18.7011	**0.5473**	0.4562	55.1187	68.5803	5.0033

Table 4. Image quality assessments for images (VOC2012) with sparse semantic correspondence. Style transfer methods [57, 58, 129] are added into the comparison with deep feature-based color transfer methods.

	Brisque	ClipIQA+	CNNIQA	DBCNN	MUSIQ	NIMA
He *et al.* **[34]**	15.0921	**0.6196**	0.0267	61.1413	64.7623	**4.8631**
Li *et al.* **[57]**	22.6553	0.3684	-0.1323	44.7962	61.6292	4.7261
Li *et al.* **[58]**	19.6063	0.5484	0.5826	56.3891	64.8212	4.5883
Yoo *et al.* **[129]**	**26.4714**	0.4951	-0.6518	43.0262	60.2921	3.9442
Lee *et al.* **[50]**	20.3232	0.6133	**0.8194**	**62.8112**	**67.8432**	4.4631

by L-channel adjustment. It is better than [34] even the latter improved by the deep feature analysis. Above all, we found that it is difficult to balance exposure while maintaining image details in low lighting condition.

6.4 Quantitative Analysis

For evaluation of color transfer methods, test datasets and related quantitative analysis tools should be provided. The mainstream test datasets include ImageNet [17], COCO [61], MIT-Adobe-5K [11], VOC2012 [20], Zero-DCE [29] and LOL [111]. The ImageNet is a comprehensive dataset that contains semantic objects with various categories. The COCO dataset are used to implement semantic and scene recognition and segmentation. The images in COCO dataset include clear semantic boundary that is useful to build recognition model. MIT-Adobe-5K includes images with color editing by artist. Zero-DCE and LOL are collected from images with different lighting conditions.

For color transfer evaluation, subjective and objective image assessments can be used to provide quantitative analysis. The subjective image assessment is more consistent with human visual perception. Perceptual visual quality can be evaluated by subjective viewing tests with mean opinion score (MOS) [103], differential mean opinion score (DMOS) [125], and single stimulus continuous quality evaluation (SSCQE) [2]. They are used in the domain of quality of experience. However, they are time consuming, laborious and expensive, since the

Table 5. Image quality assessments for images with abnormal exposure.

	Brisque	ClipIQA+	CNNIQA	DBCNN	MUSIQ	NIMA
Reinhard *et al.* **[88]**	24.3433	0.5409	0.4385	53.0969	64.3143	4.0913
Neuman *et al.* **[75]**	23.8763	0.4014	**0.9551**	**61.8065**	63.8095	4.4838
He *et al.* **[34]**	22.6033	0.6073	-1.2098	48.2776	59.9581	**4.5795**
Lee *et al.* **[50]**	20.7661	0.5451	0.0765	54.2608	59.2583	4.2567
Liu *et al.* **[66]**	**26.4591**	0.5331	0.6366	55.4791	65.5233	4.2576
Guo *et al.* **[29]**	25.2691	**0.6615**	0.6539	58.6136	**70.7592**	4.3312

Fig. 17. Color Transfer based on low lighting image enhancement. First row: color transfer results by [34] (same to instances in Figure 16); second row: color transfer results by [34] with enhancement [29].

resultant judgements require many observers with repeated testing [62]. Therefore, some researchers attempt to design objective image assessments to implement the simulation of human visual perception, including Brisque [73], ClipIQA+ [109], CNNIQA [44], DBCNN [134], MUSIQ [45], and NIMA [102]. We collect test images from COCO2017 [61], VOC2012 [20] and Zero-DCE datasets [29]. It includes three parts: images with close semantic correspondence, images with sparse semantic correspondence, and image with abnormal exposure. For the first part, we collect about 300 pairs of images from the COCO dataset artificially. The quantitative analysis is reported in Table 2. We randomly select about 1600 images (include source and target images) from the COCO and VOC datasets to build the second part. The image quality assessments are shown in Tables 3 and 4. For the last one, we randomly select about 1000 images (700 images with abnormal exposure are selected as source dataset) from the Zero-DCE dataset that contains images with different quality of exposure. The quantitative results are provided in Table 5.

7 DISCUSSION

According to the comparisons and related exploration for different technical routes, we exhibit the characteristics of different kinds of color transfer methods. It can be clearly found that the deep learning-based technical solution becomes more popular for semantic-based color transfer and special target color transfer. For semantic-based color transfer, deep features are used to represent the semantic object primarily. However, the quality of the deep feature-based color transfer method is lower than dense correspondence-based one which is reported in Table 2.

Fig. 18. Exposure correction by reverse rendering (generated in software Set.a.light 3D). A: underexposure instance; B: overexposure instance; C: exposure correction result; D: original 3D scene.

The reason is that the global parameters can be estimated by the dense correspondence when the images share similar semantic objects or regions. The deep features just represent low-level semantic relationships. Therefore, the quantitative results of HaCohe2011 [30] are better than He2018 [34] and Lee2020 [50]. For multi-parameters optimization, deep structures are implemented for color transfer with special target such as lighting optimization, contrast enhancement, etc. Such methods mainly optimize global parameters for color distribution. Naturally, they can achieve better results shown in Tabel 5. Statistical color transfer methods are focus on low-dimensional color information. The significant disadvantage of the methods is that they cannot establish flexible color mapping according to semantic objects. Nevertheless, mandatory statistical color matching increases the robustness for images with sparse correspondence. The evidence is given in Tabel 3. Compared to the style transfer methods, deep feature-based color transfer methods keep better semantic consistency. For real photo-based property transfer tasks, deep feature-based color transfer methods achieve higher scores of image quality assessments that have been proved in Table 4.

Based on the overview of the methods, we discuss the two issues in color transfer tasks. Firstly, the color transfer for images without close semantic correspondence should be considered seriously. Even the semantic analysis performance has been improved by new deep learning frameworks, it still cannot be guaranteed that each object can be recognized in the image. Especially for the images with complex semantic objects, the quality of color transfer is reduced with high probability. The global color distribution and local color correspondence can not provide reliable color scheme in such conditions, which are shown in Fig. 14. An intuitive solution is to improve ability for semantic analysis by using a larger image database with consistent lighting condition to generate the optimized reference. Another potential solution is to provide a semantically independent color transfer based on accurate color distribution. Discontinuous color distribution should be avoided like first instance by [34] in Fig. 14. It controls serious performance degradation due to semantic recognition problems.

Secondly, the low lighting enhancement should be combined with color transfer. In fact, the visualization of color distribution in image is closely related to lighting condition. The low lighting state affects the natural presentation in the real scene. Therefore, the overexposed or underexposed images should be corrected based on the illumination. The quality of the color transfer can be effectively improved. In Fig. 17, we use the image enhancement to improve the quality of color transfer method in low lighting condition. The color distributions in target images are improved to be more natural. It should be noticed that Fig. 17 just show some simplest instances for the combination. The preservation of some details may lead to the loss of other details in different regions with different exposures. One instance is shown in Fig. 16. The fourth instance by Liu *et al*. [66] keeps better details around buildings but lost details in the sky. The difficulty of the intelligent combination is that the accurate analysis for color correction with different lighting conditions require sufficient and precise inputs like material, light source, color standard, view point, etc. It can be regarded as reverse rendering task. To solve the problem, rendering technology should be introduced as important reference information. A more radical scheme is to realize scene reconstruction and introduce artificial light source to enhance specific semantic object. An instance is shown in Fig 18.

In future work, more accurate lighting model and large dataset with various color distributions should be used to generate target images. In addition, some new neural networks like transformer [68], masked autoencoder [33], variant GAN [18] and practical graph neural network [116] should be considered to improve the accuracy and flexibility for the color transfer. In particular, with the development of AI-Generated Content (AIGC), color transfer technology is intuitively important for enhancing the visual perceptual quality of generated image. Currently, AIGC related methods with latent encoding are widely used. By learning from a large number of samples to effectively model the data distribution, combined with the low-frequency signal correspondence of latent encoding, it becomes efficient to generate visually perceptible and semantically coherent content. If color transfer can be integrated into AIGC with independent learning in color space, it would add a new dimension to AIGC-related applications. In addition, the relevant techniques of color transfer can achieve the decoupling of semantic content and color distribution, which is of great value for improving the visual effects of generated content. Color distributions and semantic consistency with a cross-optimization can support more flexible content generation strategies.

In this paper, we provide a survey for image-based color transfer. The related fundamental theories and general model are explained at first. The appropriate color space enables decoupled representation for color information. It is useful to implement accurate color mapping between images. Some mainstream technical routes are introduced as follow. Benefit from deep learning tools, the semantic detection has been improved into the practical level in recent works. The mature frameworks can detect semantic correspondence for the color transfer. Some transfer results by different methods are shown in comparisons. Even with great achievements provided by new technologies, two main issues for current methods should be considered, including unstable performance for images without close semantic correspondence and influences produced by low lighting condition. The new color transfer solution should address the two key issues.

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