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Short Paper

Aesthetic Enhancement via Color Area and Location Awareness

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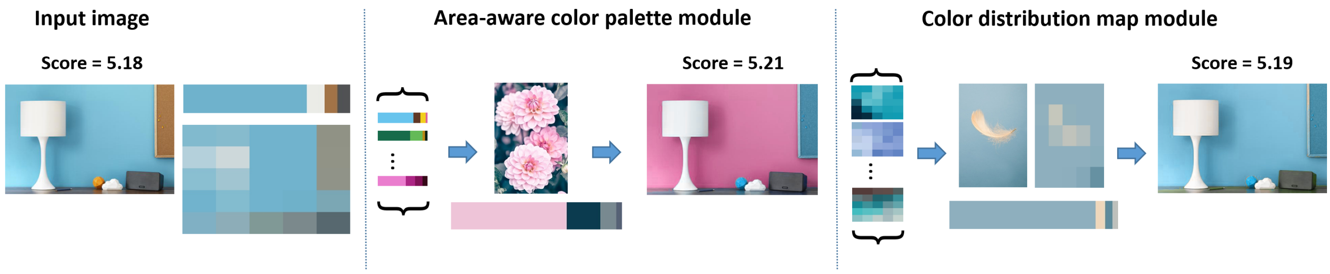

Figure 1: *Overview of our contribution-aware color transfer method for image aesthetic enhancement. Based on the area-aware color palette and color distribution map of an input image, our method automatically selects a suitable reference images among all high aesthetic images in our dataset, and transfers its coloring to improve aesthetic quality of the input image.*

Abstract

Choosing a suitable color palette can typically improve image aesthetic, where a naive way is choosing harmonious colors from some pre-defined color combinations in color wheels. However, color palettes only consider the usage of color types without specifying their amount in an image. Also, it is still challenging to automatically assign individual palette colors to suitable image regions for maximizing image aesthetic quality. Motivated by these, we propose to construct a contribution-aware color palette from images with high aesthetic quality, enabling color transfer by matching the coloring and regional characteristics of an input image. We hence exploit public image datasets, extracting color composition and embedded color contribution features from aesthetic images to generate our proposed color palettes. We consider both image area ratio and image location as the color contribution features to extract. We have conducted quantitative experiments to demonstrate that our method outperforms existing methods through SSIM (Structural SIMilarity) and PSNR (Peak Signal to Noise Ratio) for objective image quality measurement and no-reference image assessment (NIMA) for image aesthetic scoring.

Keywords: Color palette, color transfer, image recoloring, image aesthetic enhancement.

1. Introduction

Color is important to human perception on images, e.g., contributing to recognition memory [WSG02] and visual attention [JOvW*05]. Recently, many people participate in social media as YouTubers to publicize their interests or promote products. Having an easy and effective mechanism to improve the color aesthetic of video contents definitely help them enhance the attractiveness of their media presentations and attract more audience without requiring them to spend tremendous amount of time for color editing.

To improve image aesthetics, we exploit public image datasets, collecting color palettes and embedded color contribution features from high aesthetic images to form the inputs for color transfer. The proposed contribution features comprise image area ratio and image location. They constitute key factors to determine the most suitable coloring information for enhancing the aesthetic quality of an input image. We assume by transferring color palettes and features from highly aesthetic images to an input image, it will effectively improve image visual quality. Our main contributions include:

- To our knowledge, we are the first to enhance image aesthetic by transferring color combinations from high aesthetic image.
- We propose to match the color contribution features of an input image, namely color area ratio and color location, for identifying a suitable reference image for color transfer.

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2. RELATED WORK

Image Coloring and Aesthetics: Color is fundamental to characterize image aesthetic quality [OAH11]. Many studies have investigated the relationship between coloring and image aesthetics [OAH11, NOSS11, GLS16, YWF*19]. Due to public color dataset availability [colb, kul], data-driven approaches become popular for identifying favorable color combinations, i.e., color palettes, to improve image aesthetic [OAH11, COSG*06, PFC17, YWF*19]. Some works transferred colors from a reference image to modify the coloring of an input image, e.g., [CJC15] identified images with similar visual contents and geo-locations to form the references, by minimizing a cost function based on color, spatial distance and texton histograms of the purposed superpixel structure for color transfer. [XXHT18] alternatively introduced an adaptive edge indicator function on top of color distributions to avoid geometrical structure details being over-smoothed from the color transfer process. Recently, [WX20] applied salient feature mapping to control color transfer by matching the regional saliency between reference and input images. However, they focuses on color mapping between images without considering image aesthetics.

Image aesthetic assessment: Among extensive studies [DLT17], NIMA [TM18] has developed an effective no-reference image quality assessment method based on convolutional neural network. Essentially, NIMA is a generic image quality evaluation criteria, comprising quality factors (blur, noise) and aesthetic factors (color difference, contrast). If we only adjust image coloring without altering other quality factors, including noise, blur and distortion, NIMA can then be used to effectively measure image aesthetic quality difference due to color change. Since our work aims to exploit public image datasets, collecting color themes and embedded color contribution features from images with high aesthetic quality to form the inputs for color transfer, NIMA is a suitable choice to assess image aesthetics for supporting reference image selection.

Regional Image Coloring: Image coloring is location dependent. For instance, in an image of countryside scenery, one may expect having blue on top and green at bottom to represent sky and grassland. To this end, [NOSS11] has shown that local coloring has a significant impact to image aesthetics. [APCB19] proposed to learn object-dependent color distribution from image datasets, such that objects in re-colored images will be with natural colors. Recently, [LPKB20] has proposed training a region composition graph to learn relationship between local image regions for predicting local aesthetic scores through graph convolution. These scores are aggregated to produce the final image aesthetic scoring. These works generally suggested that regional color features are critical to image context and aesthetic quality. Therefore, it is essential to take regional coloring into account when performing color transfer.

3 Our Method

We propose the contribution-aware color transfer method for enhancing image aesthetic quality. As illustrated in Figure 1, our method proposes the area-aware color palette module and the color distribution map module, which can respectively match with the coloring and the regional structure of an input image to enhance its aesthetic quality based on a chosen reference image.

3.1 Our Dataset and Area-aware Color Palettes

We collect images with high aesthetic scores out of the 3600+ images from the Color Palettes website [cola] to construct our dataset, since the website provides a large number of visually appealing images. NIMA [TM18], a no-reference image assessment, is used for image aesthetic assessment, which rates an image with a score between 0 (the least aesthetic) and 10 (the most aesthetic). We select images with scores > 5, which include 2968 images, to constitute our dataset. To construct our dataset, we process the images by extracting their major color composition characteristics through color segmentation. An area-aware color palette and a color distribution map are then generated for each image and are stored together with the images to form our dataset.

Color Segmentation Map: To efficiently determine best-matching color palettes and color distribution maps for color transfer, we construct color palettes and color distribution maps using a small number of colors only. To evaluate the suitable set of colors and their area contribution, we adopt an unsupervised convolutional neural network based method [Kan18] to segment the image. However, its output is noisy as in Figure 2(b), with various levels of the same color, e.g., blues, making the image perceptually confusing. We then apply a two-step optimization to refine the output, retaining perceptually important colors only as in Figure 2(d).

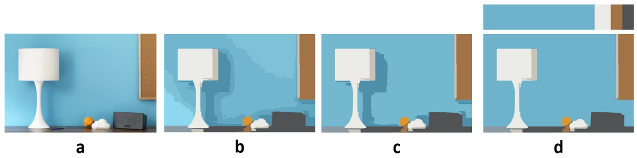

Figure 2: *Color segmentation map generation: (a) Sample input image, (b) Output from [Kan18], (c) first optimization result, (d) Final area-aware color palette and color segmentation map.*

Two-Step Optimization: In the first step, for the colors obtained by segmentation, we merge colors that look very similar under human perception, which is evaluated by the CIEDE2000 color difference [LCR01] in L*a*b color space. To implement, for each of all color pairs, we calculate the color difference between them, generating a list of color difference. Based on this, for each pair of colors c_x and c_y with CIEDE2000 color difference falling below a threshold, we merge them into one color c_{new} as follows:

$$c_{new} = \frac{n_{cx}}{\sum_{i=1}^{m} n_i} * (b_x, g_x, r_x) + \frac{n_{cy}}{\sum_{i=1}^{m} n_i} * (b_y, g_y, r_y) \tag{1}$$

$$n_{new} = n_{cx} + n_{cy} \tag{2}$$

where (b_x, g_x, r_x) and (b_y, g_y, r_y) are the RGB color values of colors c_x and c_y, respectively. n_{cx}, n_{cy} n_i are the number of pixels contributed by colors c_x, c_y, and i, respectively. m is the total color number. The merged color c_{new} will occupy n_{new} pixels. Then, a new list of colors with their corresponding number of pixels is obtained. This step will repeat until no more color pair can be merged.

The second optimization is similar in the spirit yet merging color pairs with very close hue while having brightness difference. We identify such color pairs based on the following equation:

$$\triangle E_{xy} = \sqrt{(a_x - a_y)^2 + (b_x - b_y)^2} \tag{3}$$

where the color difference $\triangle E_{xy}$ is measured by the hue distance between colors c_x and c_y with (l_x, a_x, b_x) and (l_y, a_y, b_y) being their L*a*b color space representations, respectively. For each color pair with a very small $\triangle E_{xy}$, we merge them by:

$$c_{new} = \frac{n_{cx}}{\sum_{i=1}^{p} n_i} * (l_x, a_x, b_x) + \frac{n_{cy}}{\sum_{i=1}^{p} n_i} * (l_y, a_y, b_y) \quad (4)$$

$$n_{new} = n_{cx} + n_{cy} \quad (5)$$

where p is the resultant number of colors after the first optimization. These equations are similar to Equations 1 and 2, except that they merge colors based on L*a*b color space. We also repeat this optimization step until no more color pair can be merged. Through the two-step optimization, we eventually obtain a refined color segmentation map for a given image, as illustrated in Figure 2(d).

Area-aware Palette: By collating color information from the color segmentation map, we can obtain the area-aware color palette. From the perspective of visual psychology, colors contributing small image area ratios have little influence to human perception. To refine the color palette by retaining only perceptually important colors, we empirically eliminate colors contributing less than or equal to 5% of the image area for the sake of efficiency. We may consider applying Just Noticeable Difference (JND) Estimations [WMF*16] as a future work. Finally, we obtain the area-aware color palette for each dataset image, where a color palette comprises q different types of colors, maintaining by a list of colors $C = \{c_1, ..., c_q\}$ and their corresponding area contributions $A = \{a_1, ..., a_q\}$. To proceed with color transfer, we identify a suitable reference image, where the color contribution ratios of its area-aware color palette are highly similar with those of the input image. A simple way for such a measure can be done by cosine similarity.

Color Transfer: The area-aware palette only captures global coloring characteristics, we still need a mechanism to map and transfer colors from the selected reference palette to an input image. To improve color transfer quality, we exploit the L*a*b and HSV color spaces to make color transfer device independent and to retain the overall tendency of colors of the input image, respectively. For each pixel in the input image, we map it to the color of the selected reference palette with the smallest color distance. Such a color distance is computed by the Euclidean distance based on the a and b components of the L*a*b color space, where L represents brightness while a and b represent color balance. We utilize the L*a*b color representation since it has the widest color space among others and is device-independent. Hence, a and b of L*a*b become natural choices for measuring suitable replacement colors from reference palette as they can accurately measure color relationship. We may regularize such a measurement by adding the L component weighted by a small scalar to discourage colors of large brightness differences being mapped.

Based on the mapping, we transfer colors from the reference palette to the input image accordingly to the HSV (H: color feature; S: saturation; V: brightness) color space. Straightly speaking, we replace colors by changing the H values without changing the S and V values. Because the tone refers to the overall tendency of the colors in an image, which affects how the colors are perceived by human. To retain this tendency, we only change the hue values and keep the original brightness and purity of the input image.

3.2 Color Distribution Map

To further facilitate image aesthetic enhancement, inspired by [NOSS11], we introduce the color distribution map to capture regional image coloring with a quantized representation, supporting fast retrieval of the best-fit reference image for color transfer. To generate a color distribution map, we take the color segmentation map described in Section 3.1 as the input and divide the map into a $n \times n$ grid, where $n = 1, 2, 3, \ldots$, etc. Obviously, it is not worth to use a very large n since it literally produces a color distribution map resembling the input color segmentation map. For each grid cell, we perform k-means clustering (with k = 1) over the colors inside the cell based on the proximity of color distance. The representative color of each grid cell can then be determined. Based on this, we have pre-generated and stored the corresponding color distribution maps for all images in our dataset.

To perform color transfer, we identify a most suitable reference image, which has the best-fit color distribution map to that of the input image, i.e., these color distribution maps are perceptually very similar to each other. From user perspective, this means the foreground and background of both images are similar with each other in terms of color area contributions and regional coloring structure. For implementation, we adopt a light-weight perceptive hash (pHash) measurement [CRMLR17], which uses low-frequency discrete cosine transform (DCT) coefficients to capture perceptual features of an image. If two images have very close (or the same) pHash values, these images are perceptually almost identical (or equivalent) from the user point of view, even the images may be computationally different, e.g., being modified by compression, watermarking, or comprising different number of colors, etc.

As shown in Figure 3, we perform color transfer on an input image based on different color contribution characteristics through area-aware color palette (2^{nd} column), color segmentation map (3^{rd} column), and $n \times n$ color distribution maps (for $n = 3, 4, 5$ as in 4^{th}-6^{th} columns, respectively). We compare the quality of resultant output images based on NIMA score [TM18], SSIM (Structural SIMilarity) and PSNR (Peak Signal to Noise Ratio) [FSDH14, HLSKJK14]. Clearly, results obtained by applying color distribution maps are better in quality because their higher NIMA, SSIM and PSNR scores. Note that despite the selected reference images are structurally different from the input image with respect to image background and foreground, their corresponding color distribution maps are much similar in coloring structure. Due to the lower complexity of color distribution maps, it is more efficient for retrieving a suitable reference image based on color distribution map rather than relying on color segmentation map.

4 Experiment Results

We have conducted a number of experiments to demonstrate the significance and effectiveness of our method. We measured our results based on objective metrics, including PSNR (Peak Signal to Noise Ratio) and SSIM (Structural SIMilarity) [FSDH14, HLSKJK14] for image quality measurement and no-reference image assessment (NIMA) [TM18] for image aesthetic scoring. PSNR and SSIM are very popular metrics for judging image quality. PSNR is usually used in the context of judging how well a com-

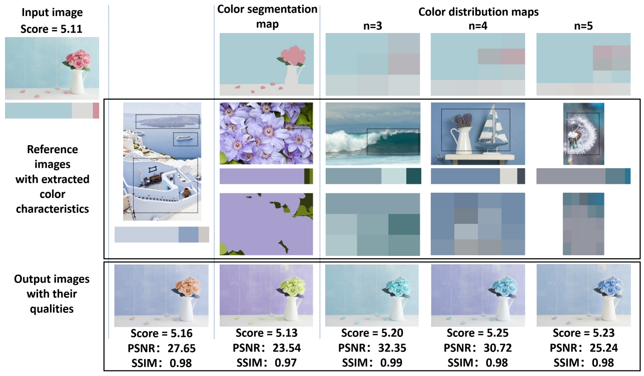

Figure 3: *Color transfer comparison: Given an input image, color transfer results are obtained based on (2^{nd} column) area-aware color palette, (3^{rd} column) color segmentation map, and (4^{th}-6^{th} columns) color distribution maps.*

Table 1: *Color transfer quality with different scenarios.*

Method	Field		Parrot		Morning Glory	
	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR
Reinhard et al. [RAGS01]	0.65	13.35	0.73	12.22	0.77	13.51
Xiao et al. [XM06]	0.80	19.64	0.81	15.73	**0.95**	10.60
Petit et al. [PKD07]	0.81	15.87	0.78	12.44	0.63	12.87
Rabin & Papadakis [RP15]	0.85	16.14	0.81	12.57	0.68	11.56
Gu et al. [GLZ20]	0.95	23.08	**0.92**	**23.10**	0.86	20.39
Our Method	**0.98**	**24.16**	0.89	18.15	0.76	**26.01**

pressed image can preserve the variance of image signals. Alternatively, SSIM is designed to judge image quality based on luminance, contrast and structure, offering a better and more generic measurement to image quality. In our context, as we do not modify image structure, applying SSIM in our experiments can effectively judge image quality based on coloring related factors, i.e., luminance and contrast. Since PSNR and SSIM measure image quality based on color signals rather than directly measuring human perception on image aesthetic, we additionally include NIMA to form another objective metric, which can evaluate image aesthetic based on human perception.

Comparison of Color Transfer Quality: To transfer colors from a reference image (or its color palette) to an input image, it is critical that such a color transfer process should not distort image contents. In other words, the process will not assign inappropriate colors to certain image regions unexpectedly. We now showcase how our proposed method outperforms existing methods [RAGS01, XM06, PKD07, RP15, GLZ20] through three test cases as shown in Figure 4, which involved different input images, namely Field, Parrot and Morning Glory, respectively. Along with these visual comparisons, in Table 1, we also depict the corresponding quantitative results based on SSIM and PSNR.

As shown in Figure 4 (top), [RAGS01, XM06, RP15] have distributed red color inappropriately to cover significant parts of image foreground contents, causing perceptual distortion. Petit et al. [PKD07] has even transferred red color to cover some clouds,

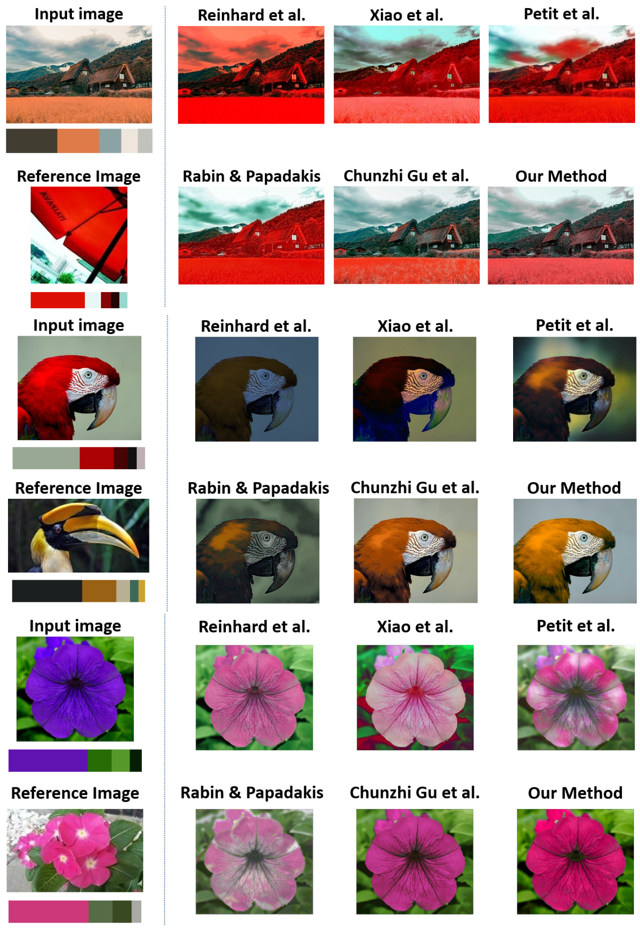

Figure 4: *Comparing based on "Field" (top), "Parrot" (middle) and "Morning Glory" (bottom).*

damaging realism. Qualitatively, the above results produce images with lower aesthetic quality. Interestingly, the result from Chunzhi Gu et al. [GLZ20] is on par with that of our method, yet producing over-saturated red. As in Table 1, our method quantitatively outperformed other methods based on SSIM and PSNR scores.

With the Parrot image in Figure 4 (middle), Chunzhi Gu et al. [GLZ20] and our method have produced the best color transfer outputs visually. This observation has also been confirmed with the higher SSIM and PSNR values achieved by these methods. Meanwhile, with the Morning Glory image in Figure 4 (bottom), except Petit et al. [PKD07] and Rabin & Papadakis [RP15], the other results are all visually natural enough, yet they are in different colors. The SSIM and PSNR measurements as shown in Table 1 can confirm these findings as both [PKD07] and [RP15] obtained the lowest SSIM values. Although our method has only achieved an average SSIM, it has still performed the best in terms of the PSNR value. Our result suggests that our generated Morning Glory image is perceptually satisfactory. The focus of this part of experiments is to verify the capability of our method in producing sufficiently natural images from the proposed color transfer process. The aesthetic assessment to our method will be presented as follows.

Comparison of Aesthetic Quality: To evaluate the aesthetic quality of our generated results, we have conducted experiments against recent relevant methods, namely 1) reference image based, 2) reference color palette based and 3) reference style based. In the experiments, the reference images used in our method are selected automatically, with the corresponding area-aware color palettes or color distribution maps is generated accordingly to facilitate experimental comparison. For fair comparison, the input images of our experiments are chosen based on the representative images used in the corresponding existing methods.

1) Reference image based methods: To perform color transfer, a popular approach is transferring colors from a reference image. Based on this, Chunzhi Gu et al. [GLZ20] implemented a global color transfer method by utilizing the Gaussian Mixture Model (GMM) to extract image color distribution and casting color transfer as a parameter estimation problem in GMM. Alternatively, He et al. [HLC*19] proposed a local color transfer method by progressively estimating dense correspondence of deep convolutional neural network features between input and (semantically similar) reference images. By contrast, our method was able to choose suitable high aesthetic images as references and extracted their corresponding area-aware color palettes to perform color transfer. As shown in Figure 5 (top), our results have obtained better NIMA scores than [GLZ20] and [HLC*19], i.e., achieving high aesthetic quality. Apart from this, the result from He et al. [HLC*19] was visually distorted, particularly the lamp shadow was mostly removed.

2) Reference color palette based methods: Some existing work perform color transfer by modifying image color palette. Junho Cho et al. [CYMLYC17] applied a multi-task network to extract the relationship between image content and its color palette for guiding color transfer. In contrast, Chang et al. [CFL*15] assumed color transfer was image content independent. It therefore applied simple mapping functions to separately change color and luminance information of an image color palette for guiding image color transfer. Similar to [CYMLYC17], our method also exploits image content features for color transfer, yet we choose color area and location contributions as the key features rather than extracting deep image features, which is more expensive. Figure 5 (middle) has shown that our method produced higher image aesthetic quality. In contrast, Chang et al. [CFL*15] has generated an overexposed image.

3) Reference style based: Following the line of transferring deep features of images [HLC*19] as discussed above in the reference image based methods, some existing work added image style as another feature to exploit texture patterns or local features for transferring semantic coloring from a reference image to an input image. Gatys et al. [GEB16] extracted the correlations across the various filter channels in each layer of the convolutional neural network as a Gram matrix to model image texture patterns. Li et al. [LW16] replaced the Gram matrix, i.e., feature statistics, with Markov random fields (MRFs) constraint to explore local image patch features for semantic coloring transfer. Luan et al. [LPSB17] alternatively resorted Matting Laplacian to enforce locally affine in color space for the transfer process on top of [GEB16]. By contrast, our method directly transfer image coloring on the pixel-level based on color contribution. In this experiment, we transfer image coloring based on color distribution map for comparing existing methods.

Figure 5 (bottom) has shown that our method produced higher image aesthetic quality. More importantly, our method did not induce image content distortion. However, with [GEB16], obvious texture pattern distortion appeared on the duvet, while the straight line showing the lighting from the right window was significantly distorted, since this method was only good for handling artist paintings rather than images with real-life scenes. [LW16] generated an image with a higher aesthetic quality than [GEB16], yet suffering from patchy artifacts, particularly along the footboard slat. This could be caused by the MRFs constraint that it applied. [LPSB17] has fixed the distortion problem from [GEB16], despite its output image was with a lower aesthetic quality.

Figure 5: *Results comparison with reference image based (top), reference color palette based (middle) and reference style based methods (bottom).*

Deep learning methods, including [HLC*19], [GEB16] and [LW16] are typically prone to visual distortion, unless some local coloring transfer constraints such as the Matting Laplacian in [LPSB17] can be adopted. Notably, direct pixel-level based color transfer, such as our proposed method, could effectively avoid such visual distortion problem.

5 Conclusions

Our method, for the first time, improves image aesthetics by transferring contribution-aware color palettes and color distribution maps generated from auto-selected high aesthetic images. Our dataset can be used as a benchmark contributing to the community. Experiments have shown that results from our method are higher in visual quality than those generated from relevant recent works. Our limitation is that if a reference image mainly comprises very similar colors, undesired outputs may be resulted if those similar colors were mapped to very different colors in an input image, due to the quantization problem. Our future work will explore the semantic relationship between images to enhance color transfer quality.

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