IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received May 14, 2020, accepted May 26, 2020, date of publication June 4, 2020, date of current version June 16, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3000065

Color Transfer With Salient Features Mapping via Attention Maps Between Images

ZONGSHENG WU [1] **AND RU XUE** [2]
[1]School of Computer Science, Xianyang Normal University, Xianyang 712000, China
[2]School of Information Engineering, Xizang Minzu University, Xianyang 712082, China

Corresponding author: Ru Xue (joywinjam@163.com)

This work was supported in part by the Natural Science Foundation of Tibet Autonomous Region under Grant XZ2018ZR G-64.

ABSTRACT Color transfer is a useful image editing technology that transfers the color style of a reference image to a source image. In this paper, a novel automatic perception color transfer method based on salient features mapping was proposed. Firstly, the saliency maps of the reference image and source image are built to predict the human visual attention regions. Secondly, the gradient map is calculated by convolving the image pair with Sobel filter. Thirdly, the saliency map and gradient map are combined to produce a weighted attention map. Fourthly, by thresholding the attention map the reference image and the source image are segmented into regions of salient and non-salient pixels, and mean and standard deviation of these two regions are calculated in the three channels of the YUV space, respectively. Finally, on the salient and non-salient pixels an execution similar to Reinhard's is performed, and the two results are combined to generate the final output. The experiments result show the superiority of our method by its pleasant natural appearance with color similarity and image details preservation, high time efficiency and easy implementation.

INDEX TERMS Color transfer, color style, salient features, gradient map, image editing.

I. INTRODUCTION

Color transfer is an image editing technology aiming to transfer the color style of a reference image to a source image, which is widely used in various image and video processing applications, such as image colorization, image enhancement and special effects for videos. Two key issues involved in this topic include the construction of correct color mapping between the reference image and the source image, and the preservation of the source image content after color transfer. Color mapping ensures that the color of the reference image be properly transferred to the source image while keeping the color similarity; and the preservation of color content requires that the structure and texture of the resulting image be consistent with source image after the process.

Over the past years, much efforts have been made to address these issues with many results. Color transfer methods can be classified into two main categories: the global color transfer methods and the local ones. The global color transfer methods [1]–[8] take into account all pixels for calculating the color statistics; it is easily used due to its simplicity and high running speed. It usually works under the assumption of similarity of global color distributions between the reference and source images. However, the typical ignorance of spatial relationship could easily cause misleading color mapping and color distortion. To achieve good results for these global methods, a careful choice of image pairs is inevitable.

In order to attack the above problems, some local color transfer methods considering the color correspondence and spatial relationship are presented in [9]–[25]. The local color transfer methods are divided into two groups: traditional methods and machine learning methods. Dominant color mapping [9], Gaussian Mixture Models [10]–[12], directive local color transfer methods [13], [14], probabilistic moving least square algorithms [15], [16], local texture-based method [17], etc. belong to the former group. The latter group includes color style changed with neural network [18], deep learning framework [19], and colorization with the SVM algorithm [20]. These local color transfer methods can also be classified as automatic methods [4], [12], [18]–[21] and interactive methods [17], [22]–[25], where the former ones refer to the automatic local color mapping without manual intervention to region matching, and the latter means the allowance of users in defining the correspondence by sketches or rectangles. Compared with global color transfer

The associate editor coordinating the review of this manuscript and approving it for publication was Inês Domingues.

methods, local methods usually work better in processing the textures and salient regions of an image. However, most local methods still have some disadvantages, such as misleading local color mapping and loss of details, which is worth further studying.

To improve the performance of the color transfer, some algorithms based on salient regions and gradient-preserving themes have been proposed. Salient regions refer to parts visually more conspicuous than the surrounding regions [26]. According to the salient regions of human visual attention in images, the color correspondence between image pairs can be built automatically. Xia [21] proposed an automatic perception aligned color transfer algorithm based on saliency-guided manner. Xiao and Ma [6] and Wang *et al.* [7] presented gradient-preserving color transfer method and L0 gradient-preserving color transfer method respectively to preserve the source image color similarity and image details.

In this paper, a novel color transfer method with salient features mapping based on the saliency map and the gradient map is proposed to achieve a pleasant natural appearance. Firstly, the saliency maps of the reference image and source image are built to predict the human visual attention regions in the images. Secondly, the gradient map is obtained by a convolution of the image pair with the Sobel filter. Thirdly, a weighted attention map is produced by a combination of saliency map and gradient map. Fourthly, by thresholding the attention map regions of salient and non-salient pixels in the reference and source images are obtained, and mean and standard deviation of these two kinds of pixels in the three channels of the YUV color space are calculated respectively. Finally, color transfer is processed by an approach similar to Reinhard's for the two kinds of pixels, whose results are added to generate the final output image. The flowchart of our approach is shown in Figure 1.

The rest of this paper is organized as follows: The related work of the color transfer methods is reviewed in Section 2. Section 3 describes in detail the proposed color transfer method with salient features preservation based on the saliency map and gradient map. The experimental results and discussions are provided in Section 4. Finally, the conclusions are summarized in the last section.

II. RELATED WORK

Reinhard *et al.* [1] firstly proposed a global color transfer method based on simple statistics of the mean and standard deviation for all pixies in the image pairs. However, due to the large difference in the characteristics of local regions between images, the performance of this method is much affected by the little similarity and sizes of the reference and source images. In the case of different color distribution, the results may look unnatural, less to say the distortion in the scene details and color distribution. As such, various improved algorithms had been proposed hence after.

Pitie *et al.* [3] proposed an N-dimensional probability density function (PDF) transfer method for global color transfer, which ensures the preservation of color distribution. However, it easily overstretches pixel values and causes content changes. As such, a softening scheme was used to remedy it. Rabin *et al.* [27] presented a nonlocal Yaroslavsky spatial filter to suppress artifacts while preserving image details. Xiao and Ma [6] proposed a gradient-preserving approach that employed a global histogram matching algorithm forcing the identity of color histograms of the resulting image with the source image. Su *et al.* [28] presented a similar color histogram matching based on the color mapping scheme. Luan *et al.* [29] introduced a deep learning method to map reference image colors to the source image. Liu and Pei [30] proposed a texture-aware emotional color transfer method between images, which can adjust an image with an emotion word or a reference image to guarantee the color gradient and naturalness. Xie *et al.* [31] designed a new color transfer model with an adaptive second-order total generalized variation (TGV) regularizer. Song and Liu [32] proposes a new image appearance transfer method combining both color and texture features, which can obtain sufficient appearance transfer results. Wang *et al.* [7] presented a $\mathscr{L}0$ gradient-preserving color transfer method which forced the consistence of pixel gradients of the color region in the resulting image with that in the source image and emphasized the similarities between source image pixel colors. The method used similarity-preserving color mapping algorithm to maintain the similarities between pixel color and dominant color. Then the $\mathscr{L}0$ gradient-preserving algorithm is performed to relax the large gradients of the sparse pixels along color region boundaries and preserve the small gradients of pixels within color regions. To some extent, this method can preserve the image details and color similarity between images. To achieve a more accurate color transfer utilizing meaningful dense correspondence between images, He *et al.* [8] used neural representations for matching and optimized a local linear model for color transfer to satisfy both local and global constraints. Generally speaking, the performance of the global color transfer algorithm depends on the similarities of color distribution between image pairs. Large statistical difference produces the unnatural effect, while the similar color statistics guarantees a perfect result.

To overcome the limitation of the global mapping algorithms, some local mapping algorithms were proposed which relied on the color correspondence and spatial relation. In the strategy of these algorithms, the correspondences of representative colors (such as dominant colors in [5], [10], [33], [34], image patch colors in [35], feature point colors in [15]) from the reference image to source image were obtained firstly. Then, the correspondence of the pixel colors between the image pairs was propagated by using techniques such as GMM and radial basis function interpolation.

Tai *et al.* [10] proposed a local color transfer method based on their soft color segmentation algorithm. Firstly, the EM algorithm was improved to segment the input images probabilistically and the Gaussian mixture model (GMM) was constructed for them. Then, the color mapping relationship between each Gaussian component in the source image and

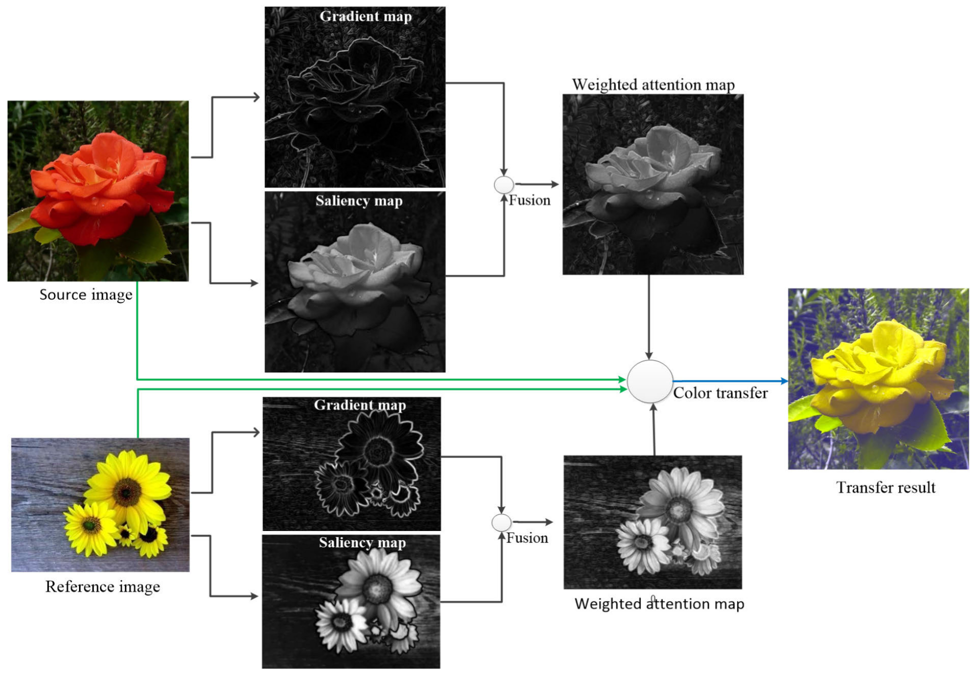


FIGURE 1. Flowchart of our approach.

some Gaussian components in the reference image were obtained. Finally, Reinhard's method was applied to each Gaussian component pair and combined the intermediate results fractionally according to the probability of each pixel.

Jin *et al.* [36] proposed a fused color transfer method for image colorization to solve the spatial color coherency problem. They employed a simple color transfer method with DFT and variance features to obtain the preliminary colorization results with incoherent colors. Fu *et al.* [37] presented a method for transferring colors between portrait images. They used a trained neural network to extract facial masks and encoded the low-frequency colors by vectoring the image pair with the sparse diffusion curves. Also, the high-frequency details in images are represented by the Laplacian of residual colors. Based on the Simple Linear Iterative Clustering (SLIC) color clustering of the input image and the reference image, Fan *et al.* [38] proposed an intention construction model for color transfer with the subjective perception to predict background and saliency regions.

Although the above color transfer methods have achieved remarkable performance, there are also some limitations in some scenarios. Global or local color statistics, and interactive manual coloring are mainly considered in these algorithms, and their performance and visual results are distinct. Here the automatic construction of the color mapping relationship is crucial to color transfer. In reality, the human visual system tends to focus on salient objects, regions, and feature edges in the image, and the saliency map presents the visual attention of the human vision to the important regions of images in the perception process. However, the saliency map - driven color mapping approach for color transfer is rarely studied. In addition, the color mapping, based on the salient feature region, qualifies a more natural visual result and easy implementation by discarding the manual selection of the mapping color in the process. In our work of the approach of an automatic correspondence color mapping via attention maps is verified by its pleasant natural results, easy implementation and lower computation cost. In the following part, our algorithm is derived from the idea of color mapping in terms of salient feature region and applied to the global and local color transfer. Experiments results show the preference of our methods to popular approaches.

III. ALGORITHM

In this section, the framework of our algorithm is described in detail. YUV color space, the algorithms for calculation of saliency map and gradient map, and the proposed color transfer method are introduced, respectively.

A. COLOR SPACE CONVERSION

Since the choice of color space often influence the image processing result, it is important to choose a proper color space for the given task. Though Lab and HSV color spaces are usually used for color transfer, we choose to use the YUV color space in this study. Different from Lab that is defined in log space, YUV model is defined in linear space. Our experiments on different color spaces indicate a preferrence to YUV color space according to its more natural appearance for most images. The comparison results generated by our method using Lab and YUV color space are shown in Figure 2.

FIGURE 2. Color space comparisons in Lab and YUV. The first column images are source images, the second column images are reference images, the third column images are transfer results in Lab, and the fourth column images are transfer results in YUV.

The YUV color model imitates human vision. Similar to RGB, YUV color space is also a kind of color-coding method, which was developed to provide compatibility between color and black/white analog television systems. YUV color space is separated into three components, i.e., Y, U and V component. The Y component determines the brightness of the color (i.e., luminance or luma), while the U and V components determine the color itself (i.e., chrominance or chroma). Without UV information, the images can be displayed with the full contents, though it is only gray (black/white).

The image is converted from RGB to YUV space according to formula (1) before making color statistics. And after the color transfer operation, the result is converted back to RGB space using formula (2).

$$\begin{pmatrix} Y \\ U \\ V \end{pmatrix} = \begin{pmatrix} 0.299 & 0.0587 & 0.114 \\ -0.148 & -0.289 & -0.437 \\ 0.615 & 0.515 & -0.100 \end{pmatrix} \bullet \begin{pmatrix} R \\ G \\ B \end{pmatrix} \tag{1}$$

$$\begin{pmatrix} R \\ G \\ B \end{pmatrix} = \begin{pmatrix} 1 & 0 & 1.140 \\ 1- & 0.395 & -0.581 \\ 1 & 2.032 & 0 \end{pmatrix} \bullet \begin{pmatrix} Y \\ U \\ V \end{pmatrix} \tag{2}$$

B. SALIENCY MAP AND GRADIENT MAP

The salient regions in the reference image and the source image are utilized for color mapping in our algorithm. To enhance the saliency of the image features, the gradient information and salient information of the reference and source image are combined. The methods for obtaining the saliency map and gradient map are described as follows.

SALIENCY MAP. The saliency of an image is the perceptual quality that makes a person, object, or pixel stand out from its neighbors and thus capture our attention. The saliency map of the image is used to predict the human visual attention regions, and many saliency detection methods have been presented. The algorithm proposed by Achanta *et al.* [39] is employed to calculate the saliency hereafter because of its simplicity and effectiveness. For the convenience of calculations, we modified the algorithm by using the YUV color space. Firstly, calculate the mean values of the pixels in the three channels of YUV space, separately. Then perform Gaussian filtering with a 5×5 separable binomial kernel on the input image to eliminate fine texture details as well as noise or coding artifacts, and split it into three color channels. Finally, obtain the saliency map by calculating the normalized Euclidean distance for each pixel using formula (3).

$$SM\,(x, y) = \left\| I_m - I_{gc}(x, y) \right\| \tag{3}$$

where I_m is the mean value of the input image. $I_{gc}(x, y)$ is the corresponding image pixel value in the Gaussian blurred version of the original input image. $\|\cdot\|$ is the L2 norm (i.e., the Euclidean distance). The norm of the difference is adopted because we are only interested in the magnitude of the differences.

To extend formula (3), we rewrite it to formula (4) and formula (5) for calculating the saliency map of the reference image (SM_{ref}) and the saliency map of the source image (SM_{src}), respectively.

$$SM_{ref} = (Y - Y_m)^2 + (U - U_m)^2 + (V - V_m)^2 \tag{4}$$

$$SM_{src} = \left(Y' - Y'_m\right)^2 + \left(U' - U'_m\right)^2 + \left(V' - V'_m\right)^2 \tag{5}$$

where Y, U, and V are the pixel values in the color channels of the Gaussian blurred reference image. Y_m, U_m, and V_m are the mean values of the pixels in the color channels of the original reference image. Similarly, Y', U', V', and Y'_m, U'_m, V'_m are corresponding values in the three color channels of the source image. Finally, SM_{ref} and SM_{src} are normalized.

GRADIENT MAP. Image gradient is the changing of gray levels along the horizontal or vertical direction. The changes are encoded by the gray levels of the horizontal or vertical component of the gradient image: the mean gray level means no change, the bright levels mean change from a dark value to bright value, the dark levels mean change from a bright value to dark value. The image gradients and edges are usually extracted by using the Sobel operator in image processing applications.

The Sobel operator is an edge detection filter, which results in the image emphasizing edges. The edge is where the pixel values change the most, which is one of the salient features of the image and plays an important role in image feature extraction, object detection, pattern recognition and etc. The Sobel operator is a separable filter that is represented by two 3×3 convolution kernels. Both kernels have the same coefficients as they are rotated 90 degrees to each other and can provide maximum value at horizontal or vertical edge orientation. We can get the x- and y- directional gradients of an image by using the Sobel filter to convolve the image.

Calculate the x-directional gradients with the Sobel operator in the horizontal (x) direction using formula (6).

$$G_x = \begin{vmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{vmatrix} \bullet I(x, y) \tag{6}$$

Calculate the y-directional gradients with the Sobel operator in the vertical (y) direction using formula (7).

$$G_y = \begin{vmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{vmatrix} \bullet I(x, y) \tag{7}$$

where $I(x, y)$ is the gray grayscale image of the input image.

After obtaining the vertical and horizontal gradients, these two components are combined to produce the magnitude of the gradient using formula (8).

$$G = \sqrt{G_x^2 + G_y^2} \tag{8}$$

Finally, the gradient map GM is obtained by normalizing the G value.

C. COLOR TRANSFER ALGORITHM

In our algorithm, the input images are the reference image I_r and the source image I_s, and the output of the algorithm is the transferred image I_o. Firstly, the input images are converted into YUV color space. Then, we compute the saliency map SM_{ref} and SM_{src} of the reference image I_r and source image I_s, respectively. Meanwhile, the gradient map GM_{ref} and GM_{src} of the reference image I_r and source image I_s are calculated. Next, a weighted combination of gradient map and saliency map is used to produce attention maps M_{rw} and M_{sw} for the reference image and the source image respectively according to formulas (9) and (10).

$$M_{rw} = 0.5^* SM_{ref} + 0.5^* GM_{ref} \tag{9}$$

$$M_{sw} = 0.5^* SM_{src} + 0.5^* GM_{src} \tag{10}$$

where SM_{ref} and GM_{ref} are the saliency map and gradient map of the reference image. SM_{src} and GM_{src} are the saliency map and gradient map of the source image.

After obtaining the weighted attention maps, the pixels in the reference and source image are segmented into salient pixels and non-salient pixels by a small threshold according to formulas (11) through (14).

$$I_{ry} = I_r(M_{rw} \geq \theta) \tag{11}$$

$$I_{rn} = I_r(M_{rw} < \theta) \tag{12}$$

$$I_{sy} = I_s(M_{sw} \geq \theta) \tag{13}$$

$$I_{sn} = I_s(M_{sw} < \theta) \tag{14}$$

where I_{ry} and I_{rn} denote the salient pixels and non-salient pixels in the reference image. I_{sy} and I_{sn} denote the salient pixels and non-salient pixels in the source image. θ is the threshold for segmenting the salient pixels and non-salient pixels, here $\theta = 0.01$ is determined by experiments.

Next, the mean value and standard deviation of the salient pixels and non-salient pixels in three channels of YUV space are calculated separately. A similar method to Reinhard *et al.* [1] is adopted to perform the color transfer. We use the reciprocal of the scaling factor proposed in [1] to scale the difference value between the pixel value and mean value. This method produces results more consistent, aesthetical and pleasing.

The color transfer operation for the salient pixels is performed as follows:

$$I_{oy}(x, y) = (I_{sy}(x, y) - m_{sy})\frac{\sigma_{sy}}{\sigma_{ry}} + m_{ry} \tag{15}$$

where, m_{sy} and m_{ry} are the mean value of the salient pixels in the source and reference images in three channels, respectively. Similarly, σ_{sy} and σ_{ry} denote the standard deviation of the salient pixels in the source and reference images in YUV channels.

Likewise, the color transfer operation for the non-salient pixels is performed as follows:

$$I_{on}(x, y) = (I_{sn}(x, y) - m_{sn})\frac{\sigma_{sn}}{\sigma_{rn}} + m_{rn} \tag{16}$$

where, m_{sn} and m_{rn} are the mean value of the non-salient pixels in the source and reference images in YUV space, respectively. Similarly, σ_{sn} and σ_{rn} denote the standard deviation of the non-salient pixels in the source and reference images of the three channels.

The final output result is obtained by adding the color transfer results of the salient pixels and non-salient pixels with formula (17).

$$I_o(x, y) = I_{oy}(x, y) + I_{on}(x, y) \tag{17}$$

Finally, $I_o(x, y)$ is clipped to the range [0, 255] and converted from YUV to RGB color space.

IV. RESULTS AND DISCUSSION

In this section, extensive experiments have been carried out to evaluate the performance of the proposed method. Our algorithm was implemented with Python and OpenCV and run in Windows 7 environment on a laptop with Intel Core i7 2.60 GHz processor and 8GB RAM.

A. PERFORMANCE EVALUATION

In the first experiment, the performance of the proposed method and state-of-the-art automatic color transfer approaches was evaluated on 70 reference-source image pairs as the test examples. Each image pair includes a source image and a reference image. The proposed method was compared with five baseline methods: Pitie *et al.* [4], Xiao and Ma [6], Rabin *et al.* [27], Su *et al.* [28], and Wang *et al.* [7].

Some of these examples we used are the same as that of Wang *et al.* and the comparison results produced by these methods are shown in Figure 3.

In the illustrated examples, there are different color distributions between the source and reference images. Nevertheless, our proposed method can achieve good natural results. Moreover, the color similarity and detail features are preserved in the results.

From Figure 3, it can be observed that our results in the first and second columns are similar to Wang's but better than others. The results generated by our method in the third and fourth columns have more natural appearances. Furthermore, the proposed method has more advantages in execution speed.

The second experiment evaluated the performance of the color mapping schemes by comparing our method with the color histograms matching [6], probabilistic color mapping [28] and $\mathscr{L}0$ gradient-preserving scheme [7], separately. These schemes were tested on 50 image pairs. Each image pair generated an intermediate image by conducting only the color mapping step. The results of three representative examples are shown in Figure 4.

FIGURE 3. Comparisons of the proposed method with Pitie *et al.* [4] (n = [10,10,3,3,10], $\psi = 1$), Xiao and Ma [6] ($\lambda = 1$), Rabin *et al.* [27], Su *et al.* [28] and Wang *et al.* [7]. The first row images are reference images; the second row images are source images.

FIGURE 4. **Color mapping comparisons. Our method is compared with those using color histogram matching (Xiao *et al.*), probabilistic color mapping (Su *et al.*), and $\mathscr{L}0$ gradient-preserving scheme (Wang *et al.*).**

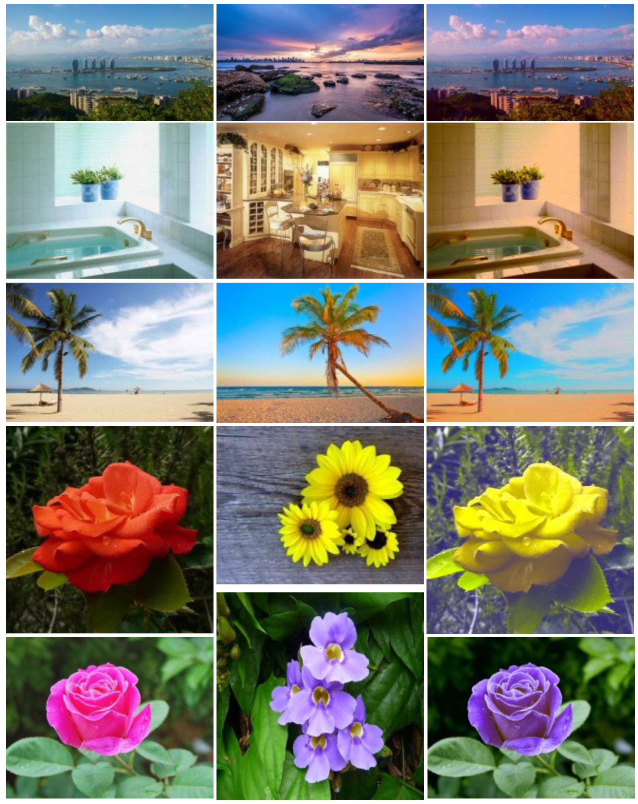


FIGURE 5. **More examples of our approach. The first column images are source images, the second column images are reference images, and the third column images are transfer results.**

In these examples, the results produced by our method appear to have more natural visual effects than the other schemes. Compared with the $\mathscr{L}0$ gradient-preserving scheme and ours, the visual effect of the results generated by the color histograms matching and probabilistic color mapping scheme is relatively inferior, such as the part in the left column sky, the grass and the sky in the middle column, and the maple leaves in the right column. Moreover, the proposed method has better color similarities than Wang *et al.* about the building color in the left column and the sky color in the middle column. Furthermore, the proposed method has better visual performance than the others in detail preservation. For example, the building in the first column and the leaves in the right column are more distinct in detail.

Figure 5 shows more examples of our proposed color transfer method. From this figure, the first row and second row are the global color mapping scenarios, which achieved excellent color transfer effects. The image pairs in the third to fifth row are the local color mapping scenarios. In the third row, the colors of the coconut tree and beach in the reference image are transferred to the corresponding part of the source image correctly. In the examples of the last two rows, the primary goal is the local color transfer between the flowers. It can be observed that the colors of the flowers in reference images are transferred to the source images accurately. The results have a natural pleasant appearance. Furthermore, the details of the transfer results are excellent.

B. TIME CONSUMPTION

In addition to the performance of the algorithm, the running speed is also a factor in consideration. In this experiment, 30 image pairs were tested to evaluate the run-time of our proposed method, Xiao and Ma [6], Su *et al.* [28], and Wang *et al.* [7]. We uniformly resized all the images to the size of 800×600. The run-time in the form of mean and standard deviation (SD) for all compared methods is shown in Table 1. The mean value of the run-time for all image pairs is shown in the first row, and the standard deviation (SD) is given in the second row. Obviously, the run-time of our proposed method is far less than other methods for color transfer. Because our method is simple to implement, it can run very fast reasonably.

The entire color transfer of our proposed method takes about 0.16 seconds to produce the final result for an 800×600 input image, while the other methods take much higher time. For example, the method of Wang *et al.* takes more than 8 seconds. Those CNN (convolutional neural network) based

TABLE 1. Run-time comparison for color transfer.

	Xiao et al.[6]	Su et al. [28]	Wang et al.[7]	Ours
Parameter	$\lambda=1$	n=3, k=8	-	-
Time(s)	2.18	5.65	8.16	**0.16**
SD	0.13	0.23	0.28	0.02

color transfer methods require higher hardware configuration while consumes more run-time.

The experimental results show that the proposed approach has a significant advantage in time consumption compared with the color transfer methods based on the color histograms matching, probabilistic color mapping, and gradient-preserving method.

C. LIMITATIONS

From the experimental results, the proposed method has achieved remarkable performance on image pairs where semantical correspondence is significant, such as the examples in the bottom two rows of Figure 4. Moreover, for most of the image pairs without salient semantic features the visual effect of our method is also slightly better than some traditional methods, though not so remarkably, as shown in Figure 2 and Figure 3.

However, for some image pairs where the saliency for one is background, and the other is foreground, the proposed method may produce poor visual effects due to incorrect color mapping.

V. CONCLUSION

The color transfer between images is a useful image processing technology. Successful color transfers can accurately transfer the color style from the reference image to the source image while preserving the color similarity and the details of the source image. In this paper, we have proposed a novel color transfer method with salient features mapping between the reference and source images based on human visual perception. The color transfer is performed in the YUV color space. It maps the colors of salient feature regions based on the saliency map and the gradient map. Our method is simple and easy to implement with low time cost. Moreover, the proposed method is suitable for most of some scenes of the global and local color transfer, which has good robustness and can achieve a pleasant natural appearance with color similarity and image details retained. Furthermore, the proposed method can be applied to the video content easily because of its easy implementation and high speed. To solve the limitations of the proposed algorithm, we will make efforts to improve it further in future work.

REFERENCES

[1] E. Reinhard, M. Adhikhmin, B. Gooch, and P. Shirley, "Color transfer between images," *IEEE Comput. Graph. Appl.*, vol. 21, no. 4, pp. 34–41, Jul./Aug. 2001.

[2] X. Xiao and L. Ma, "Color transfer in correlated color space," in *Proc. ACM Int. Conf. Virtual Reality Continuum Appl. (VRCIA)*, Hong Kong, 2006, pp. 305–309.

[3] F. Pitie, A. C. Kokaram, and R. Dahyot, "N-dimensional probability density function transfer and its application to color transfer," in *Proc. 10th IEEE Int. Conf. Comput. Vis. (ICCV)*, Beijing, China, vol. 2, Oct. 2005, pp. 1434–1439.

[4] F. Pitié, A. C. Kokaram, and R. Dahyot, "Automated colour grading using colour distribution transfer," *Comput. Vis. Image Understand.*, vol. 107, nos. 1–2, pp. 123–137, Jul. 2007.

[5] Y.-W. Tai, J. Jia, and C.-K. Tang, "Soft color segmentation and its applications," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 29, no. 9, pp. 1520–1537, Sep. 2007.

[6] X. Xiao and L. Ma, "Gradient-preserving color transfer," *Comput. Graph. Forum*, vol. 28, no. 7, pp. 1879–1886, Oct. 2009.

[7] D. Wang, C. Zou, G. Li, C. Gao, Z. Su, and P. Tan, "*L*0 gradient-preserving color transfer," *Comput. Graph. Forum*, vol. 36, pp. 93–103, Oct. 2017.

[8] M. He, J. Liao, D. Chen, L. Yuan, and P. V. Sander, "Progressive color transfer with dense semantic correspondences," *ACM Trans. Graph.*, vol. 38, no. 2, pp. 1–18, Apr. 2019.

[9] W. Dong, G. Bao, X. Zhang, and J.-C. Paul, "Fast local color transfer via dominant colors mapping," in *Proc. ACM SIGGRAPH ASIA Sketches (SA)*, 2010, p. 46.

[10] Y.-W. Tai, J. Jia, and C.-K. Tang, "Local color transfer via probabilistic segmentation by expectation-maximization," in *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2005, pp. 747–754.

[11] Y. Xiang, B. Zou, and H. Li, "Selective color transfer with multi-source images," *Pattern Recognit. Lett.*, vol. 30, no. 7, pp. 682–689, May 2009.

[12] M. Grogan and R. Dahyot, "L2 divergence for robust colour transfer," *Comput. Vis. Image Understand.*, vol. 181, pp. 39–49, Apr. 2019.

[13] L. Florea and C. Florea, "Directed color transfer for low-light image enhancement," *Digit. Signal Process.*, vol. 93, pp. 1–12, Oct. 2019.

[14] Z. Li, Z. Tan, L. Cao, H. Chen, L. Jiao, and Y. Zhong, "Directive local color transfer based on dynamic look-up table," *Signal Process., Image Commun.*, vol. 79, pp. 1–12, Nov. 2019.

[15] Y. Hwang, J.-Y. Lee, I. S. Kweon, and S. J. Kim, "Color transfer using probabilistic moving least squares," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun. 2014, pp. 3342–3349.

[16] Y. Hwang, J.-Y. Lee, I. S. Kweon, and S. J. Kim, "Probabilistic moving least squares with spatial constraints for nonlinear color transfer between images," *Comput. Vis. Image Understand.*, vol. 180, pp. 1–12, Mar. 2019.

[17] B. Arbelot, R. Vergne, T. Hurtut, and J. Thollot, "Local texture-based color transfer and colorization," *Comput. Graph.*, vol. 62, pp. 15–27, Feb. 2017.

[18] Q. Chen, J. Xu, and V. Koltun, "Fast image processing with fully-convolutional networks," in *Proc. IEEE Int. Conf. Comput. Vis. (ICCV)*, Oct. 2017, pp. 2497–2506.

[19] D. Liu, Y. Jiang, M. Pei, and S. Liu, "Emotional image color transfer via deep learning," *Pattern Recognit. Lett.*, vol. 110, pp. 16–22, Jul. 2018.

[20] L. Cao, L. Jiao, Z. Li, T. Liu, and Y. Zhong, "Grayscale image colorization using an adaptive weighted average method," *J. Imag. Sci. Technol.*, vol. 61, no. 6, 2017, Art. no. 60502.

[21] J. Xia, "Saliency-guided color transfer between images," in *Proc. Adv. Vis. Comput.*, Berlin, Germany, 2013, pp. 468–475.

[22] C. L. Wen, C. H. Hsieh, B. Y. Chen, and M. Ouhyoung, "Example-based multiple local color transfer by strokes," *Comput. Graph. Forum*, vol. 27, pp. 1765–1772, Oct. 2008.

[23] A. Levin, D. Lischinski, and Y. Weiss, "Colorization using optimization," in *Proc. ACM SIGGRAPH*, 2004, pp. 689–694.

[24] S. Liu, H. Sun, and X. Zhang, "Selective color transferring via ellipsoid color mixture map," *J. Vis. Commun. Image Represent.*, vol. 23, no. 1, pp. 173–181, Jan. 2012.

[25] M. Grogan, R. Dahyot, and A. Smolic, "User interaction for image recolouring using £2," in *Proc. 14th Eur. Conf. Vis. Media Prod. (CVMP)*, London, U.K., Dec. 2017, pp. 1–10.

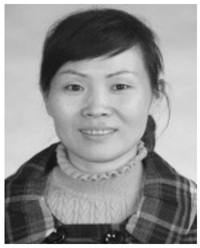
[26] R. Achanta, F. Estrada, P. Wils, and S. Süsstrunk, "Salient region detection and segmentation," in *Proc. 6th Int. Conf. Comput. Vis. Syst.*, Berlin, Germany, 2008, pp. 66–75.

[27] J. Rabin, J. Delon, and Y. Gousseau, "Removing artefacts from color and contrast modifications," *IEEE Trans. Image Process.*, vol. 20, no. 11, pp. 3073–3085, Nov. 2011.

[28] Z. Su, K. Zeng, L. Liu, B. Li, and X. Luo, "Corruptive artifacts suppression for example-based color transfer," *IEEE Trans. Multimedia*, vol. 16, no. 4, pp. 988–999, Jun. 2014.

[29] F. Luan, S. Paris, E. Shechtman, and K. Bala, ‘‘Deep photo style transfer,’’ in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jul. 2017, pp. 4990–4998.
[30] S. Liu and M. Pei, ‘‘Texture-aware emotional color transfer between images,’’ *IEEE Access*, vol. 6, pp. 31375–31386, 2018.
[31] B. Xie, C. Xu, Y. Han, and R. K. F. Teng, ‘‘Color transfer using adaptive second-order total generalized variation regularizer,’’ *IEEE Access*, vol. 6, pp. 6829–6839, 2018.
[32] Z.-C. Song and S.-G. Liu, ‘‘Sufficient image appearance transfer combining color and texture,’’ *IEEE Trans. Multimedia*, vol. 19, no. 4, pp. 702–711, Apr. 2017.
[33] H. Chang, O. Fried, Y. Liu, S. DiVerdi, and A. Finkelstein, ‘‘Palette-based photo recoloring,’’ *Acm Trans. Graph.*, vol. 34, no. 4, pp. 1–11, 2015.
[34] Q. Zhang, C. Xiao, H. Sun, and F. Tang, ‘‘Palette-based image recoloring using color decomposition optimization,’’ *IEEE Trans. Image Process.*, vol. 26, no. 4, pp. 1952–1964, Apr. 2017.
[35] Y. HaCohen, E. Shechtman, D. B. Goldman, and D. Lischinski, ‘‘Non-rigid dense correspondence with applications for image enhancement,’’ *ACM Trans. Graph.*, vol. 30, no. 4, pp. 1–10, Jul. 2011.
[36] Z. Jin, L. Min, M. K. Ng, and M. Zheng, ‘‘Image colorization by fusion of color transfers based on DFT and variance features,’’ *Comput. Math. Appl.*, vol. 77, no. 9, pp. 2553–2567, May 2019.
[37] Q. Fu, Y. He, F. Hou, J. Zhang, A. Zeng, and Y.-J. Liu, ‘‘Vectorization based color transfer for portrait images,’’ *Comput.-Aided Des.*, vol. 115, pp. 111–121, Oct. 2019.
[38] M. Fan, Z. Li, and J. Long, ‘‘Color transfer based on visual saliency,’’ in *Proc. Adv. Graphic Commun., Printing Packag.*, Singapore, 2019, pp. 227–232.
[39] R. Achanta, S. Hemami, F. Estrada, and S. Susstrunk, ‘‘Frequency-tuned salient region detection,’’ in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun. 2009, pp. 1597–1604.

ZONGSHENG WU received the B.S. degree in computer science from the Xi’an University of Technology, Xi’an, Shaanxi, China, in 1998, the M.S. degree in traffic information engineering and control from Chang’an University, in 2012, and the Ph.D. degree in mechanical and electronic engineering from the Xi’an University of Technology, in 2017. He is currently an Assistant Professor with the School of Computer Science, Xianyang Normal University, Xianyang, Shaanxi, China. His main research interests include swarm intelligent optimization, digital image processing, intelligent robot, and robot vision.



RU XUE was born in Xi’an, Shaanxi, China, in 1974. She received the B.S. degree in computer science from the Xi’an University of Technology, Xi’an, Shaanxi, China, in 1998, the M.S. degree in communication and information system engineering from Tianjin University, Tianjin, in 2007, and the Ph.D. degree in intelligent transportation and information system engineering from Chang’an University, Xi’an, Shaanxi, in 2014.

She has 20 years of teaching and research experience. She is currently a Professor with Xizang Minzu University, Xianyang, Shaanxi, China. Her research interests include computer vision, machine learning, image processing, image steganography, and pattern recognition.