A Fast and Efficient Fuzzy Color Transfer Method

Arash Abadpour [1] and Shohreh Kasaei [2]
[1] Mathematics Science Department, Sharif Univ. of Tech., Tehran, Iran, email: abadpour@math.sharif.edu
[2] Computer Engineering Department, Sharif Univ. of Tech., Tehran, Iran, email: skasaei@sharif.edu

***Abstract*— Each image has its own color content that greatly influences the perception of human observer. Being able to transfer the color content of an image into another image, while preserving other features, (like texture), opens a new horizon in human–perception–based image processing. In this paper, after a brief review on the few efficient works performed in the field, a novel fuzzy principle component analysis (PCA) based color transfer method is proposed. The proposed method accomplishes the transformation based on a set of corresponding user–selected regions in images along with a blending ratio parameter set by the user. Results show more robustness and higher speed when comparing our proposed method with other available approaches.**

I. Introduction

Altering color appearance of an image, due to the information extracted from another image has been under investigation in recent years. *Reinhard et al.* [1] discuss that removing a dominant and undesirable colorcast (such as the yellow in the photos taken under incandescent illumination) will be a handy tool. *Chang et al.* [2] state that as each artist has its own style like the "*yellow that Van Gogh likes to use*", it will be fascinating to be able to transfer the feeling of a painting to a photograph, what they call "*giving the viewers the impression similar to that given by the painting*". *Greenfield et al.*'s work [3] is similar to *Chang et al.*'s work in spite for the fact that the two images in their method are both colored–paintings. They state their method as "*liquefy the color of a painting in such a way that it could be poured to another*".

The notion of *color transfer* is not widespread in the literature. Perhaps the first work in this field is the method developed by *Reinhard et al.* [1]. they designed a method for color transfer by choosing a suitable color space and applying the reference image's color appearance to the source image by means of some statistical parameters. The paper emphasizes that the proper choice of a suitable color space is of great importance [1]. Because when the images of the nature are represented in many typical color spaces, there is a high correlation between channels, making single channel alteration a difficult task. They choose $\ell\alpha\beta$ color space by *Ruderman et al.* [4]. *Reinhard et al.* express that the $\ell\alpha\beta$ color space has never been applied otherwise or compared to the other color spaces. Authors are not aware of any correspondence to the color space since then, rather than [1], [2], [3], [4], [5], [6]. Using the $\ell\alpha\beta$ color space, *Reinhard et al.* state their color transfer method as mapping the color vectors using first and second order statistics. They express that, as that method tries to transfer one image's appearance to another one, it is possible to select such source and reference images that do not work well. To overcome this shortcoming, they proposed to use the concept of *swatches*. In the new method, user must select some different swatches in the two images. For example the grass, the sky, and so on. Then a classification task takes place and each pixel will be altered according to the statistics of the corresponding swatches in the two images that it belongs. One of the main contributions of that work is the idea of computing the altered color vector in each of the classes and blending them inversely proportional to the distances from the initial point to each of the clusters.

Chang et al. [2] used an early work by *Berlin et al.* [7] that examined 98 languages from several families, and reported that there are regularities in the number of basic colors and their spread on the color space. They stated that in developed languages, there are eleven color terms. In English, they are *black*, *white*, *red*, *green*, *yellow*, *blue*, *brown*, *pink*, *orange*, *purple*, and *gray*. *Chang et al.*'s work [2] that is implemented entirely in the $CIE-La^*b^*$ color space, uses later works that defined the spread of these categories. Their method begins with making the 11 loci of the points in source image that belong to any of the 11 clusters. Then, they generate the convex hull that encloses all of the pixels within each of the categories. The same task is performed in the reference image. For the given vector $\vec{c}_1$ in the i–th category, the recolored vector is computed using a linear mapping between the convex hulls. It easy to see that *Chang et al.* [2] is using the same mapping idea of *Reinhard et al.* 's [1] swatches, except that the swatches are preselected in his method; although resulting in less needed user supervision, but also less adaptivity when dealing with special problems. Also, the method leaves few room for user intervention.

Greenfield et al. [3] organized the images into pyramids to produce a palette for each image by successively down–sampling it. The color transfer is then performed based on the two palettes, computed in the source and the reference images. Although, that work seems to use a different method compared with the *Reinhard et al.*'s method [1], but when they tend to transfer the actual color, they apply $\ell\alpha\beta$ color space and alter the α and β content of points, leaving ℓ unchanged, like what *Reinhard et al.* [1] have proposed. When working with multi–spectral images, data dimension is an important problem, (showing itself as a factor increasing the processing time massively). There are a few works on using dimension reduction methods in color images (*e.g.*, see [8]). Principal Component Analysis (PCA) is a fast linear dimension reduction method [9]. The basic idea behind the PCA is to find the linear transform giving the maximum

(a) (b)

Fig. 1. Typical result of the proposed color transform method. (a) Original Image. (b) Recolored Image.

amount of variance out of the set of given vectors. The axis of i–th maximum variance is denoted as $\vec{v}_i$. In practice, the computation of $\vec{v}_i$ is accomplished by using the covariance matrix $C = E\{(\vec{x} - \bar{\vec{x}})(\vec{x} - \bar{\vec{x}})^T\}$, where $\vec{v}_i$ is the eigenvector of C corresponding to the i–th largest eigenvalue [9]. In [10] the authors proposed a novel PCA–based dimension reduction method for natural color images, reducing the 3–D color space to a shifted version of a 1–D vector space. The idea is developed further to define the *linear partial reconstruction error* (LPRE) in [11]. The LPRE likelihood measure, fuzzyfication scheme, and homogeneity decision are proved to outperform the conventional *Euclidean* and *Mahalonobis* distances, dominantly [11].

In this paper, firstly, a new color transfer method is proposed that transforms the color information from the reference image to the source image, (according to one set of corresponding regions in the images). The general color transfer method uses the fusion of the set of single region recolored results, using an LPRE–based fuzzyfication technique. User contribution in our proposed method is limited to select a few corresponding regions in the reference and source image (like the swatch idea of *Reinhard et. al.* [1]), along with tuning a one–parameter membership function.

Some authors call the color transfer method as *recoloring*, but in this paper, these two terms are used interchangeable. We call the image to be recolorized and the image from which the color information is extracted as the *source* and the *reference* images, respectively. In all formulas, variables indexed as x_1 and x_2 belong to the source and the reference images, respectively. Also, variables denoted as $x_1^p rime$ are relating to the source image after colorizing task has taken place. All vectors in this paper are assumed to be column vectors.

The rest of this paper is organized as follows: Section II-A introduces the single region recoloring method, while Section II-B states the fuzzification scheme. Section II-C describes the proposed fusion technique for rendering the resulting image. Section III states the experimental results and discussions and the conclusion are given in Section IV.

II. Proposed Method

A. Single Region Color Transfer Method

Assume that the image I_1 is to be recolorized using the information in image I_2. Also, assume that the region r_1 in I_1 should pretend the region r_2 in I_2. Let the vector $\vec{\eta}_{r_1}$ denote the expectation vector of r_1 and the 3×3 matrix V_{r_1} contain the eigenvectors of the covariance matrix of r_1 as its columns sorted by corresponding eigenvalue in a descending fashion. The vector $\vec{\eta}_{r_2}$ and the matrix V_{r_2} are defined in a similar way for the region r_2 in the reference image (I_2). By modelling the color information in r_1, as an *ellipsoid* spread around $\vec{\eta}_{r_1}$, the proposed recoloring method for single selected regions in the source image and the reference image is defined as:

$$\vec{c}_1' = V_{r_2} V_{r_1}^{-1} (\vec{c}_1 - \vec{\eta}_{r_1}) + \vec{\eta}_{r_2}. \qquad (1)$$

The linear transformation described in (1), first subtracts the center of the ellipsoid from all points to move it to the center. Then using V_{r_1} which is the PCA matrix of r_1, the pixels of the source image are converted to the PCA coordinates. Using V_{r_2} and $\vec{\eta}_{r_2}$ the transformation goes in the inverse direction.

B. Fuzzyfication of Natural Color Images

In [11], the authors proposed to use the error made by neglecting the two less important principal components as a likelihood measure. In this method, the LPRE likelihood of the vector $\vec{c}$ to the cluster r is defined as:

$$e_r(\vec{c}) = \|\vec{v}^T(\vec{c} - \vec{\eta})\vec{v} - (\vec{c} - \vec{\eta})\| \qquad (2)$$

where $\vec{v}$ shows the direction of the first principal component and $\|\vec{x}\|$ denotes the normalized L_1 norm. Investigating (2) makes clear that, to make $e_r(\vec{c})$ comparable over different clusters, a normalization scheme is crucial. In [11] the authors proposed to use the following stochastic margin as the normalization factor:

$$\|f\|_{r,p} = arg_e\Big(P_{\vec{x}\in r}\{f(\vec{x}) \le e\} \ge p\Big) \qquad (3)$$

where p is the inclusion percentage. Equation (3) leads to the definition of the normalized likelihood function:

$$\tilde{e}_{r,p}(\vec{c}) = \frac{e_r(\vec{c})}{\|e_r\|_{r,p}}. \qquad (4)$$

Also, the $\|e_r\|_{r,p}$ is a proper homogeneity criterion [11].

Note that $e_{r,p}(\vec{c})$ is giving lower values for the color vectors *similar* to those that exist in r. Thus, a fuzzy membership function is needed to map $[-1,1] \to [1, 1-\varepsilon]$ and $[-\infty,-1] \cup [1,\infty] \to [1-\varepsilon, 0]$. In [11], the authors proposed a manipulated form of the well–known low–pass *Butterworth* filter for the sake of tunability and simplicity, as:

$$B_{\alpha,\beta}(x) = \Big(1 + \big(\frac{x}{\tau_{\alpha,\beta}}\big)^{2N_{\alpha,\beta}}\Big)^{-\frac{1}{2}} \qquad (5)$$

where $N_{\alpha,\beta}$ and $\tau_{\alpha,\beta}$ are defined as:

$$N_{\alpha,\beta} = \left[\log_2\left(\frac{\alpha\sqrt{1-\beta^2}}{\beta\sqrt{1-\alpha^2}}\right)\right] \qquad (6)$$

$$\tau_{\alpha,\beta} = \alpha^{\frac{1}{N_{\alpha,\beta}}} \left(1-\alpha^2\right)^{-\frac{1}{2N_{\alpha,\beta}}} \quad (7)$$

and $[x]$ denotes the nearest integer value to x. The function is designed in the way that satisfies $B_{\alpha,\beta}(1) = \alpha$ and $B_{\alpha,\beta}(2) = \beta$. Note that selecting a large member of $]0, 1[$ as the α value and a small member of $]0, \alpha[$ as the β value, leads to a desired fuzzyfication. Also, note that the above definition of membership functions is in contrast with the general selection of the Gaussian functions.

Regarding the definition of the normalized reconstruction error and the re–formulated Butterworth function, the source image is fuzzyficated with respect to the query region r as:

$$h_{r,\alpha,\beta} = B_{\alpha,\beta}\big(\tilde{e}_{r,p}(\vec{c})\big). \quad (8)$$

Now, the points in r and the points similar to them, in the color sense, are mostly giving membership values in the range of $[1, \alpha]$; while color information that are not like r are ranked with poor values. Thus, we set $\alpha = 0.99$ and $p = \frac{1}{2}$. Note that by tuning the β parameter, one can easily control the spread of the membership function. Now, the fuzzyfication scheme is defined as,

$$h_{r,\beta} = B_{0.99,\beta}\big(\tilde{e}_{r,\frac{1}{2}}(\vec{c})\big). \quad (9)$$

C. Multiple Region Color Transfer Method

Assume that the user has selected n corresponding regions in the source image and the reference image, respectively (call them $r_{11} \cdots r_{1n}$ and $r_{21} \cdots r_{2n}$). As discussed in Section II-A, using each set of corresponding regions, $[r_{1i}, r_{2i}]$, equation (1) gives the recolored image. We propose to blend the results using the fuzzyfication scheme proposed in Section II-B. Hence, the proposed color transfer method is formulated as:

$$\vec{c}_1' = \frac{\sum_{i=1}^{n} h_{r_{1i},\beta}(\vec{c}_1)\left[V_{r_{2i}} V_{r_{1i}}^{-1}(\vec{c}_1 - \vec{\eta}_{r_{1i}}) + \vec{\eta}_{r_{2i}}\right]}{\sum_{i=1}^{n} h_{r_{1i},\beta}(\vec{c}_1)}. \quad (10)$$

III. Experimental Results

All algorithms are developed in *MATLAB 6.5*, on a *1100 MHz Pentium III* personal computer with $256MB$ of *RAM*. Some of the sample images used in this paper are shown in Figure 2. The proposed color transform method is performed on the sample images (illustrated in Figure 2). The results of our method along with results of other methods are shown in Figure 3 . The β value and description of the selected regions in images are expressed in the caption of Figure 3. It is worth mentioning that transferring color information of a 512×512 image into a 512×512 image according to the four selected medium–sized regions only takes about 4 seconds. Comparing the results in Figure 3 (the results of our proposed method), and Figure 4 (the results of other methods) shows the performance of our proposed method. While there is a discontinuity in the sky in Figure 4–e, the sky in Figure 3–e simulates a real night sky, having in mind that the photograph is taken at daytime. This fact is more visible when one confirms that the recolorized Figure 4–e does not pretend to be a night scene while Figure 3–e does so. This is also visible in Figure 4–b where the blue sky has nothing to do with the entirely white sky of Figure 2–f. The sky in Figure 3–b is more whitened. Although, *Greenfield et al.*'s method [3] has tried to transfer the cold colors of Figure 2–g to Figure 2–c, but Figure 4–c still contains the warm *violet–blue* color on the topmost skull. In Figure 3–c the colors are mostly cold. Figure 4–d made by *Chang et al.* [2], seems acceptable in spite of the fact that the method that has produced it, is a massively expensive operation.

It also should be noted that using a reference image of entirely different scene compared with the source image does not force the process to fail, but the results of such operation must be deliberated carefully. The same event occurs when giving regions of the source image and the reference image in a scattered fashion; for example trying to transfer color information of leaves to sand.

No exact time measurement is reported in other works. Considering the 4 seconds record of our method while other methods use sophisticated jobs of segmentation and convex hull computation, the outstanding performance our proposed method is clear.

It must be emphasized that in the proposed method, using an image as the source image and the reference image at the same time (recoloring an image with itself) when working on almost the same regions in the reference image and the source image, gives an image that cannot be recognized from the original image. In addition when using single–region version of the method, the process is completely reversible.

Although in all samples discussed here the reference image was unique, there is no limitation that prevents the user from using two or more images as the reference image. This option may be useful when trying to recolor a source image due to the sky in first reference image and the leaves in second reference image.

IV. Conclusions

A new fuzzy principle component analysis based color transform is proposed and tested on different images, including 5 images adopted from previous work for the sake of performance comparison. The images synthesized by our method are more pretending the reference images when compared with other available approaches. Also, while other references did not report the time needed for their proposed methods, our proposed method's computation cost of a few seconds for 512×512 images is promising.

Acknowledgements

The first author wishes to thank Ms. *Azadeh Yadollahi* for her encouragement and invaluable ideas.

References

[1] E. Reinhard, M. Ashikhmin, B. Gooch, and P. Shirley, "Color transfer between images," *IEEE Computer Graphics and Applications*, vol. September/October, 2001.

[2] Y. Chang, S. Saito, and M. Nakajima, "A framework for transfer colors based on the basic color categories," in *Proceedings of the Computer Graphics International (CGI'03), IEEE*, 2003.

[3] G. R. Greenfield and D. H. House, "Image recoloring induced by palette color associations," *Journal of WSCG'03*, vol. 11(1), pp. February 3–7, 2003, 2003.

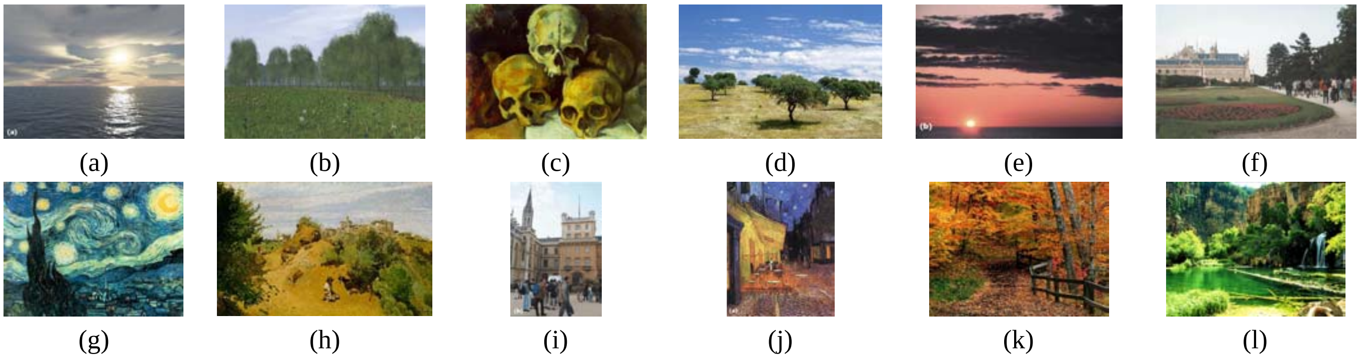

Fig. 2. Some typical sample images. (a), (b), (c), (d), (i), and (k) Source images. (e), (f), (g), (h), (j), and (l) Reference images. (a), (b), (e), (f), (i) and (j) Adopted from [1]. (c), (g) Adopted from [3]. (d), (h) Adopted from [2]. (k) "*Mc. Cormic Creck State Park, Indiana* " by *Mike Briner*, *mbphoto@spraynet.com*, *www.mikebrinerphoto.com* (adopted with permission of the author). (l) "*Hanging Lake*" by *Brent Reed*, *brent@reedservices.com* (adopted with permission of the author).

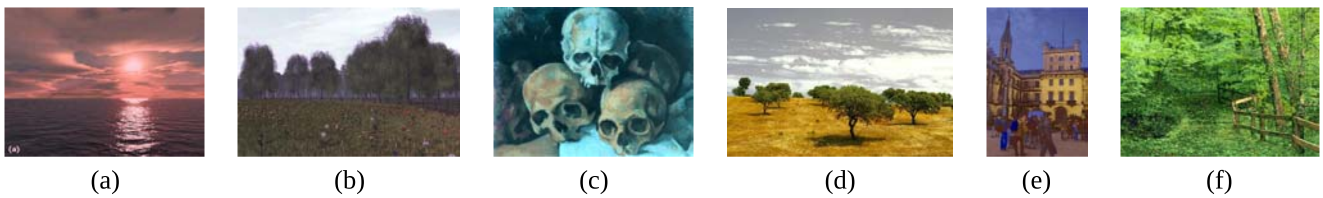

Fig. 3. Results of the proposed color transform method applied on sample images shown in Figure 2. Source images are Figures 2–a, 2–b, 2–c, 2–d, 2–i, and 2–k, respectively. reference images are Figures 2–e, 2–f, 2–g, 2–h, 2–j, and 2–l respectively. Parameters are set to values of (a) $\beta = 0.5$, $r = \{Sky, Water\}$, (c) $\beta = 0.1$, $r = \{Leaves, Sky\}$, (c) $\beta = 0.8$, $r = \{Skulls, Background\}$, (d) $\beta = 0.95$, $r = \{Leaves, Sky, Earth\}$, (e) $\beta = 0.95$, $r = \{Sky, Building, Pavement\}$, (f) $\beta = 0.2$, $r = \{Leaves, Bushes, Bark\}$.

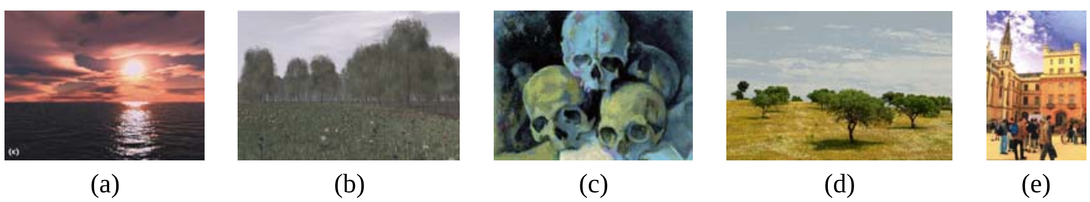

Fig. 4. Results of other available methods applied on sample images shown in Figure 2. Source images are Figures 2–a, 2–b, 2–c, 2–d, and 2–i, respectively. Reference images are Figures 2–e, 2–f, 2–g, 2–h, and 2–j respectively. (a),(b),(e) *Reinhard et al.*'s method [1]. (c) *Greenfield et al.*'s method [3], (d) *Chang et al.*'s method [2].

[4] D. Ruderman, T. Cronin, and C. Chiao, "Statistics of cone response to natural images: Implementation for visual coding," *Optical Doc. Of America*, vol. 15(8), pp. 2036–2045, 1998.

[5] W.-Q. Yan and M. S. Kankanhalli, "Colorizing infrared home videos," in *Proceedings of IEEE International Conference on Multimedia and Expo (ICME 2003)*, Baltimore, July 2003.

[6] T. Welsh, M. Ashikhmin, and K. Mueller, "Transferring color to grayscale images," in *proceedings of ACM SIGGRAPH 2002*, San Antonio, July 2002, pp. 277–280.

[7] B.Berlin and P. Kay, *Basic Color Terms, Their Universality and Evolution*. Berkeley: University of California Press, 1969.

[8] S.-C. Cheng and S.-C. Hsia, "Fast algorithm's for color image processing by principal component analysis," *Journal of Visual Communication and Image Representation*, vol. 14, pp. 184–203, 2003.

[9] A. Hyvrinen and E. Oja, "Independent component analysis: Algorithms and applications," *Neural Networks*, vol. 13(4–5), pp. 411–430, 2000.

[10] A. Abadpour and S. Kasaei, "A new parametric linear adaptive color space and its pca–based implementation," in *The 9th Annual CSI Computer Conference, CSICC*, Tehran, Iran, Feb. 2004, pp. 125–132.

[11] ——, "Performance analysis of three homogeneity criteria for color image processing," in *IPM Workshop on Computer Vision*, Tehran, Iran, 2004.