AN UNSUPERVISED FAST COLOR TRANSFER METHOD

Arash Abadpour

Sharif University of Technology
Mathematics Science Department
P.O. Box 11365-9517, Tehran, Iran
abadpour@math.sharif.edu

Shohreh Kasaei

Sharif University of Technology
Computer Engineering Department
P.O. Box 11365-9517, Tehran, Iran
skasaei@sharif.edu

ABSTRACT

Each image has its own color that greatly influences the perception of human observer. In this paper, after a very brief review of the available literature on color transfer among color images, a novel fuzzy principle component analysis (FPCA) based color transfer method is proposed that uses an efficient fuzzy clustering method. Results show more robustness and higher speed when comparing the performance of the proposed method with other available approaches.

Keywords : Image Recoloring, Fuzzy Clustering, Fuzzy Principle Component Analysis (FPCA).

1. INTRODUCTION

Color transfer among color images refers to the methods designed to change the color appearance of a color image according to another colored images color content. Different researchers use different terms to name the images taking part in this process. Here, we call the image from which the color information is extracted as the "*reference*" image, while the image on which these color information is applied is called as the "*source*" image. Finally, the source image with the the color information added to it, is called the "*destination*" image. For the sake of simplicity we address such a system as a "color transfer" or a "recoloring" one.

Reinhard, *Ashikhmin*, *Gooch*, and *Shirley* [1] are perhaps the first team to work on recoloring. They describe their core strategy as choosing a suitable color space for generating the new color in an statistical framework. They use the $\ell\alpha\beta$ [2] color space for decorrelating the color components. Firstly, they consider the whole image as a single color category and the color generator performs a linear mapping. As the paper describes, the performance of this method depends on the similarity of the two images and is likely to fail. To overcome this shortcoming, they propose to use the *swatches*. In this method, user must select two sets of corresponding swatches in the source and the reference images, then each swatch is defined as a single color category. For the given color vector, the classifier computes its *fuzzy* membership to each color category using the inverse *Euclidean* distances. Then for each category, given that the pixel belongs completely to it, the new color vector is computed and the resulting vectors are blent using the membership values. They report promising results and suggest further use of higher moments. After that *Yin*, *Jia*, and *Morrissey* [3] developed a color transfer method especially designed for face images. thus, there is no color classifier present in their work. Their proposed color generator is the same as *Reinhard et al.*'s [1] one but working in the HSI color space.

Chang, *Saito*, and *Nakajima* [4] worked on color transfer from a color painting to a color photograph. They use an early work by *Berlin* and *Kay* [5] which examined 98 languages from several families and reported that there are regularities in the number of basic colors and their spread in the color space. *Chang et al.*'s work [4] that is implemented entirely in the $CIE-La^*b^*$ color space, uses later works that defined the spread of these categories. The method begins with making the 11 loci of the points in source image that belong to each of the 11 clusters. Then, they generate the convex hull that encloses all the pixels within each of the categories. The same task is performed on the reference image. These 11 loci make the color categories, and the classification task investigates the locus inside which the given color vector exists. The color generator uses geometric mapping using the parameters of the locus to which the given color vector belongs and the corresponding locus in the reference image. As *Chang et al.* [4] use a set of fixed swatches, the method does not let any user supervision. For example the user is not allowed to add reddish reflections to the blue surface of the sea, like what occurs due to the sun shades and easily obtainable using the method by *Reinhard et al.* [1].

Greenfield and *House* [6] designed a method for color transfer among color paintings using the $\ell\alpha\beta$ color space. They organized the source and the reference images into pyramids to produce a palette for each image. They emphasize that their primary focus is not making an intelligent pallet association process and used some heuristic methods using the area occupied by each pallet color. Each pallet color serves as a color category and the classifier works in a hierarchical way to assign a pallet color to the given pixel. The color generator transfers the α and β components and then performs a color correction process to compensate for ℓ variations. While the method by *Greenfield et al.* [6] suffers from the same problem of the *Chang et al.* [4]'s approach, because of leaving no room for user intervention, they use the spatial distribution of the color vectors more professionally. They have no comment about the performance of that method for color photographs.

Abadpour and *Kasaei* [7] proposed a PCA–based color transform that uses a set of swatches in the source and the reference images. While being faster than all available approaches, the method gives no visual artifacts as visible in the results of *Reinhard et al.* [1] and *Greenfield et al.* [6]. The only shortcoming of the method by *Abadpour et al.* [7] is that an unfamiliar user may give non–homogenous swatches to the algorithm which may result in unsatisfactory destination images. The same error may happen in the method by *Reinhard et al.* [1].

Neglecting the details, all of the available color transfer methods except for the work by *Abadpour et al.* [7], use the same assumption that there exists an standard color space that performs well in decorrelating the color components. It is proved in different works (*e.g.*, [8, 9]) that none of the standard color spaces are successful in giving a decorrelated representation of the color vectors in an unconditioned imaging framework for classification or the kinds of direct manipulations mentioned here. Also, the *Euclidean* distance–based classifiers used by *Reinhard et al.* [1] has been proved to result spuriously [10].

Recently, much attention is focused on using the *principal component analysis* (PCA) for processing color images [11]. This new approach assumes color images as vector geometries and applies vectorial tools on them. This is in contrast with the general assumption about the performance of considering color images as a set of parallel grayscale images or using standard color spaces for working on them (*e.g.*, see [12, 13]). It is proved that a PCA–based color descriptor called *linear partial reconstruction error* (LPRE) is a proper model for homogenous color swatches [14]. Also, the comparison of the LPRE–based fuzzification and homogeneity decision has proved its performance over the commonly used *Euclidean* and *Mahalanobis* distance–based approaches [10]. *Abadpour* and *Kasaei* used the LPRE model to develop a cylindrical clustering method called the *fuzzy principal component analysis–based clustering* (FPCAC) [15]. Comparison of the FPCAC with the well–known *fuzzy C–means* (FCM) [16] have proved that FCM results in meaningless segments in color images, while the results of FPCAC are desirable [15]. Note that, PCA is the common axis around which the LPRE, the FPCAC [15], and the PCA–based recoloring [7] are working in the same framework. In this paper, taking advantages of the FPCAC [15] and the PCA–based color transfer method [7], we propose a new method for unsupervised color transfer.

2. PROPOSED METHOD

Assume that according to the given source image I_1 and the given reference image I_2, we have to produce the destination image I_1'. Figure 1 shows the flowchart of the proposed recoloring method. Firstly, both images are fed to the FPCAC [15]. The results of the clustering are the two sets of membership maps $J_{11}, \cdots, J_{1c}$ and $J_{21}, \cdots, J_{2c}$, describing the membership of each pixel in the source and the reference images to each of the c clusters, respectively. Note that the membership values of I_1 and I_2 pixels are measured regarding to the respective cluster parameters. Here, c is the number of the clusters which should be input to the FPCAC. In all experiments, we use three clusters, while it is observed that more number of clusters only inflates the processing time with no explicit influence on the quality of the result. The FPCAC also gives a color descriptors for each cluster in the source and the reference images. Denote them by $[\vec{\eta}_{11}, V_{11}], \cdots, [\vec{\eta}_{1c}, V_{1c}]$

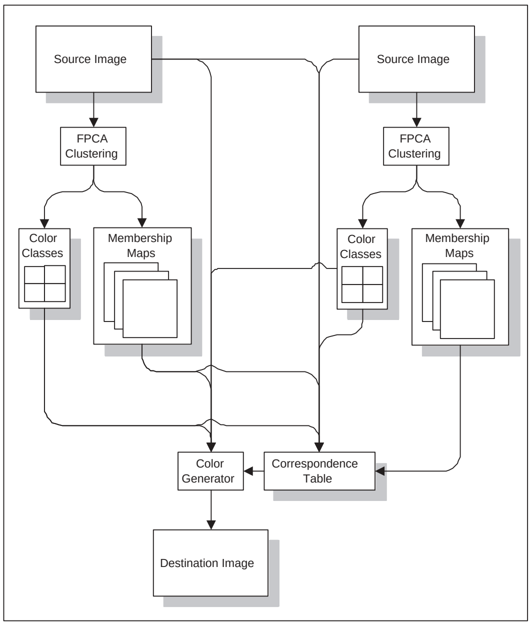


Figure 1: Flowchart of the proposed color transfer method.

and $[\vec{\eta}_{21}, V_{21}], \cdots, [\vec{\eta}_{2c}, V_{2c}]$, respectively. Here, $\vec{\eta}_{ij}$ is the fuzzy expectation of the vectors in the j–th cluster and V_{ij} denote the FPCA matrix of the j–th cluster [15].

Assume producing the crisp segmentation of the source image as the indexed image J_1. each pixel in J_1 holds an index in the range of $[1, \cdots, c]$ showing the cluster to which the corresponding pixel in the source image belongs more,

$$\forall x, y, J_1(x, y) = i \leftrightarrow \forall j \neq i, J_j(x, y) \leq J_i(x, y). \quad (1)$$

The crisp segmentation mask J_2 is produced in the same way for the reference image. Now, using all the pixels in the reference image that belong to the i–th cluster (decided by $J_1(x, y) = i$), we produce the image P_{i1}. In fact, the set of artificial images $[P_{11}, \cdots, P_{1c}]$ make a pallet for the source image. In the same way the pallet $[P_{21}, \cdots, P_{2c}]$ is produced for the reference image. Now the problem is to give an assignments between the corresponding pallet members in the source and the reference images. Although the kind of heuristic assignments that *Greenfield et al.* [6] use in their work is applicable here, but we prefer to leave this part to the user. In this way, the method incorporates the intention of the user and gives better results. It should be emphasized that when no user intervention is desirable, the pallet members could be assigned according to their respective occupied area or any other criterion. Here, we show the pallet members to the user and ask for the index array m. In this way, m_i shows that the pallet representative P_{1i} in the source image is assigned to P_{2m_i} in the destination image.

Now, for the color vector $\vec{I}_{1xy}$ in the source image, its new version $\vec{I}'_{1xy}$ is computed as,

$$\vec{I}'_1(x, y) = \frac{\sum_{i=1}^{c} \tilde{J}_{1ixy} \Big(C_{2m_i} C_{1i}^{-1} (\vec{I}_{1xy} - \vec{\eta}_{1i}) + \vec{\eta}_{2m_i} \Big)}{\sum_{i=1}^{c} \tilde{J}_{1ixy}} \quad (2)$$

where, $\tilde{J}_{1ixy}$ is the averaged version of J_{1ixy} using a convolution kernel of radius ρ. The reason for selecting $\tilde{J}_{1ixy}$ over the original J_{1ixy} is to add more blending to the vectors to prevent spurious edges. In this paper, everywhere we use $\rho = 5$. Investigating (2) shows that the new vector $\vec{I}'_1(x, y)$ is produced using a weighted sum of the altered versions of the original vector $\vec{I}_1(x, y)$ using the parameters of each category. The weights of the sum are coming from the membership maps.

3. EXPERIMENTAL RESULTS

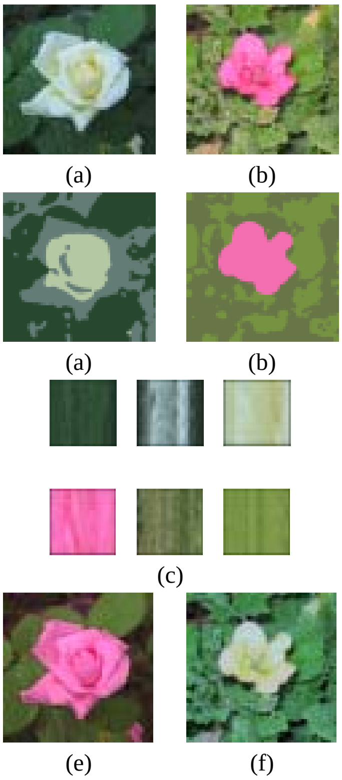


Figure 2: Results of the proposed recoloring method. (a) and (b) Original images. (c) Segmentation results of a by the FPCAC. (d) Segmentation of b by the FPCAC. (e) The corresponding pallets (Top: a, Bottom: b). (f) The destination when a is the source and b is the reference. (g) The destination when b is the source and a is the reference.

Figure 2 shows a sample run of the proposed method containing the original images along with the intermediate and final results. Here, each of the images shown in Figure 2–a and Figure 2–b are recolored using each other as the reference image. Figure 2–c and Figure 2–d show the corresponding segmentation results given by the FPCAC and Figure 2–e and Figure 2–f illustrate the corresponding pallets. When recoloring Figures 2–a according to Figures 2–b the pallet assignments is as 311 meaning that the first pallet representative in the source image is assigned to the third one in the reference image, while the two others are assigned to the first one. In the reverse transform, the assignment is also 311. Both operation take about 11 seconds.

Figure 3: Sample images. (a) and (b) Adopted from [1]. (c) and (d) Adopted from [6]. (e) and (f) Adopted from *www.webshots.com* with permission of the authors. (e) "*Mc. Cormic Creck State Park, Indiana* " by *Mike Briner*, *mbphoto@spraynet.com*, *www.mikebrinerphoto.com*. (f) "*Hanging Lake*" by *Brent Reed*, *brent@reedservices.com*. (g) and (h) Adopted from [4].

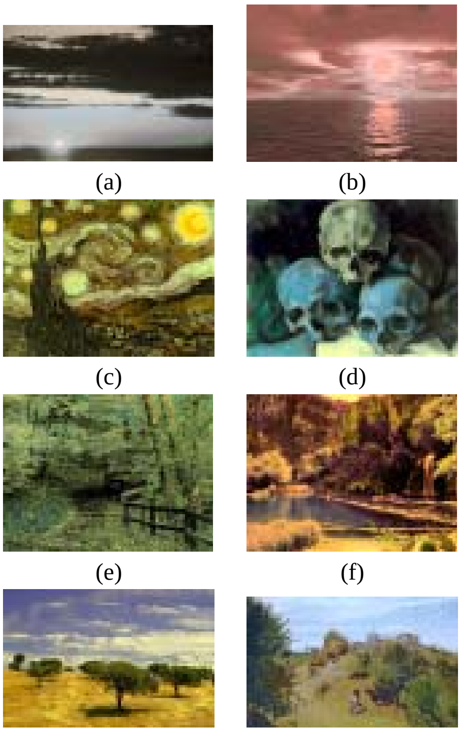
Figure 3 shows other sample images used in this paper. The proposed recoloring method is performed on all images both as the source image and the reference image. Figure 4 shows the results. Figure 5 shows a few results of other approaches which were available to the authors. Table 1 lists the corresponding source and reference images along with the elapsed times. The exact report of the time measurement is neglected in the references but considering the less than 30 seconds record of our proposed method while other methods use sophisticated methods of hierarchical segmentation and convex hull computation, the outperforming state of our proposed method is clear.

4. CONCLUSIONS

Taking advantages of PCA–based color description and clustering, a new unsupervised color transfer method is proposed. Results of the proposed method on different samples are illustrated and compared with the available literature. While the method gives satisfactory results, it is faster than other approaches.

(a) (b) (c)

Figure 5: Results of other approaches. (a) *Reinhard*, *Ashikhmin*, *Gooch*, and *Shirley* [1]. (b) *Greenfield* and *House* [6]. (c) *Chang*, *Saito* , *Nakajima* [4]. For details see Table 1.



(a) (b) (c) (d) (e) (f) (g) (h)

Figure 4: Results of the proposed method when working on the images shown in Figure 3. For details see Table 1.

Acknowledgement

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

Table 1: Description of the results shown in Figure 4 and Figure 5.

Source	**Reference**	**Destination**	**Elapsed Time (s)**
3–a	3–b	4–a	16
3–b	3–a	4–b	16
3–c	3–d	4–c	8
3–d	3–c	4–d	8
3–e	3–f	4–e	8
3–f	3–e	4–f	8
3–g	3–h	4–g	6
3–h	3–g	4–h	6
3–b	3–a	5–a	–
3–d	3–c	5–b	–
3–g	3–h	5–c	–

5. 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] 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.

[3] L. Yin, J. Jia, and J. Morrissey, “Towards race–related face identification: Research on skin color transfer,” in *Proceedings of the Sixth IEEE International Conference on Automatic Face and Gesture Recognition (FGR’03)*, 2003.

[4] 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.

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

[6] 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.

[7] A. Abadpour and S. Kasaei, “A new fast fuzzy color transfer method,” in *The 4th IEEE International Symposium on Signal Processing and Information Technology (ISSPIT 2004)*, Rome, Italy, 2004.

[8] M. C. Shin, K. I. Chang, and L. V. Tsap, “Does color space transformation make any difference on skin detection?” in *IEEE Workshop on Applications of Computer Vision*, Orlando, FL, December 2002, pp. 275–279.

[9] S. Jayaram, S. Schmugge, M. C. Shin, and L. V. Tsap, “Effects of colorspace transformation, the illuminance component,and color modelling on skin detection,” in *2004 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR’04)*, 2004.

[10] A. Abadpour and S. Kasaei, “Performance analysis of three homogeneity criteria for color image processing,” in *IPM Workshop on Computer Vision*, Tehran, Iran, 2004.

[11] 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.

[12] J. Bruce, T. Balch, and M. Veloso, "Fast and cheap color image segmentation for interactive robots," in *Proceedings of IROS–2000*, Japan, 2000.

[13] L. Lucchese and S. Mitra, "Colour segmentation based on separate anisotropic diffusion of chromatic and achromatic channels," *Vision, Image, and Signal Processing*, vol. 148(3), pp. 141–150, June 2001.

[14] 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.

[15] ——, "A new fpca–based fast segmentation method for color images," in *The 4th IEEE International Symposium on Signal Processing and Information Technology (ISSPIT 2004)*, Rome, Italy, 2004.

[16] J. C. Bezdek, *Pattern Recognition with Fuzzy Objective Function Algorithms*. New York: Plenum Press, 1981.