# Dominant color extraction based color correction for multi-view images

**Feng Shao (邵 枫), Mei Yu (郁 梅), and Gangyi Jiang (蒋刚毅)**

*Faculty of Information Science and Engineering, Ningbo University, Ningbo 315211*

Received March 20, 2007

Color information is very important in setting the style of images. In this paper, a color correction method based on dominant color extraction is proposed to eliminate the color inconsistence between multi-view images. With the theory of basic color categories, dominant colors from the categories are extracted for reference image and input image, and then the corresponding color mapping relationships are built. Experimental results show that the proposed method is quite effective.

*OCIS codes:* 110.0110, 100.6890, 330.1690.

Free viewpoint video (FVV) system is one of the most attracting applications for multi-view video processing[1]. Color correction, the process designed to transfer the color appearance of input image according to the color content of reference image, has been recognized as pivotal operation in FVV system[2]. Because multi-view image sequences are taken from different viewpoints with multiple cameras, light sources, shadows, camera aperture, exposure time, etc., may all affect the final images[3]. Then it has a significant impact on ultimate 3D display and virtual viewpoint rendering.

Reinhard *et al.* presented a pioneering work about color transfer[4]. Using the $l\alpha\beta$ de-correlated color space[5], they transferred color statistic from one image to another for coping color characteristic using the mean and standard deviation. The performance of their method depends on the similarity of the images. However, one important aspect of the color correction problem is the change of content between the target image and source image. For example, the target image may present more sky while the source image presents more oceans. Since all color correction algorithms are sensitive to the variations of color content, they risk overstretching the color mapping and thus it results in unauthentic renderings. To deal with the issue, an effective solution is to manually select swatches in both of target and source images and thus associate color clusters corresponding to the same content. In Ref. [6], the pixels of the both images are classified in a restricted set of basic color categories (BCCs), derived from psycho-physiological studies. It gives a more natural transformation but limits the range of possible color correction. Moving picture experts group-7 (MPEG-7) develops dominant color descriptor which only stores the most representative colors[7], it will provide more compact and accurate description on the distribution of colors.

In this paper, a color correction method based on dominant color extraction is proposed. First, by initial color labeling and refined color labeling, each pixel is described by one of the 11 BCCs and the corresponding probabilities. Then colors with the highest percentages are extracted from the 11 BCCs as dominant colors. Finally, color correction is implemented for input image by using dominant colors matching.

In the proposed method, the categorization of pixel is regarded as "color labeling", and color labeling method consists of two steps, the initial color labeling and the refined color labeling.

The initial color labeling method performs the following procedures, first cluster the CIELAB space into 11 BCCs using

$$D=\sqrt{(L(x,y)-\bar{L}_i)^2+(a(x,y)-\bar{a}_i)^2+(b(x,y)-\bar{b}_i)^2}, \tag{1}$$

here $L(x,y)$, $a(x,y)$, and $b(x,y)$ are values of the three color channels in CIELAB space, and $\bar{L}_i$, $\bar{a}_i$, and $\bar{b}_i$ are color values for the $i$th BCC, and $D$ is the Euclidean distance. And then label each pixel in an image according to these clusters. In the process of the initial color labeling, each pixel completely belongs to one of the 11 BCCs and the corresponding probability of belonging to the entire BCCs is 1.

The refined color labeling is performed for avoiding pseudo contours. Pseudo contour appears if input image contains some color gradation regions of which the step is over the boundary of two different BCCs and therefore the regions are divided into different categories. It leads to a problem that pixels with similar colors might be shifted to different color directions because we later transfer color of each pixel according to its category without any other location information. To solve the problem, a novel refined color labeling mechanism is proposed depending on the color difference in the input image. The calculation of one iteration step for one pixel is shown by

$${}_iP_{xy}=\frac{\sum_{(x',y')\in N}{}_iP_{x'y'}w\left(I(x,y),I(x',y')\right)}{\sum_{(x',y')\in N}w\left(I(x,y),I(x',y')\right)}, \tag{2a}$$

$$w(I(x,y),I(x',y'))=1-\frac{1}{1+\mathrm{e}^{-0.5(\mathrm{Dist}(I(x,y),I(x',y'))-T_1)}}, \tag{2b}$$

here $I(x,y)$ is the CIELAB color value of pixel $(x,y)$ with three color channels of $L(x,y)$, $a(x,y)$, and $b(x,y)$, and ${}_iP_{xy}$ is the probability that $I(x,y)$ belongs to the

 

$i$th BCC. $\mathrm{Dist}(I(x,y), I(x',y'))$ is the Euclidean distance between $I(x,y)$ and $I(x',y')$, $N$ is the set of 8-neightbour pixels of pixel $(x,y)$, and $w$ is a weighting function that goes to 1 as the color difference between $I(x,y)$ and $I(x',y')$ becomes small, and goes to 0 if becomes large. $T_1$ is a threshold related to the similarity of pixels. The iteration continues until there are no more changes while processing.

After the above operations, whole pixel in the images can be described by the 11 BCCs and the corresponding probabilities. The mean $\mu_i$ and standard deviation $\sigma_i$ belonging to the $i$th BCCs can be computed by

$$\mu_i = \sum_{x,y} {}_iP_{xy} \cdot I(x,y) \Bigg/ \left(\sum_{x,y} {}_iP_{xy}\right), \tag{3}$$

$$\sigma_i = \sqrt{\sum_{x,y} {}_iP_{xy} \cdot (I(x,y) - \mu_i)^2 \Bigg/ \left(\sum_{x,y} {}_iP_{xy}\right)}. \tag{4}$$

The percentage of the $i$th BCC occupying in the whole 11 BCCs can be described by

$$p_i = \sum_{x,y} {}_iP_{xy} \Bigg/ \left(\sum_i \sum_{x,y} {}_iP_{xy}\right). \tag{5}$$

Then $\{p_i\}$ is sorted in descending order. If the accumulative percentage $\left(\sum_{i=1}^{M} p_i\right) < T_2$, the colors with the highest $p_i$ $\{i | i \leq M\}$ is regarded as dominant colors. $M$ is the dominant color number. Here, $T_2$ is a threshold controlling dominant color number. The dominant colors is represented as

$$F = \{c_i, p_i, \mu_i, \sigma_i\}, \tag{6}$$

where $c_i$ is the $i$th dominant color; $p_i$ represents its percentage value; $\mu_i$ and $\sigma_i$ are its color mean and color standard variation.

Finally, for the reference image and input image, matching their dominant colors, and performing color correction for the pixel $I^{\mathrm{in}}(x,y)$

$$I^{\mathrm{out}}(x,y) = \sum_{i=1}^{M} p_i \left(\frac{\sigma_i^{\mathrm{ref}}}{\sigma_i^{\mathrm{in}}} \left(I^{\mathrm{in}}(x,y) - \mu_i^{\mathrm{in}}\right) + \mu_i^{\mathrm{ref}}\right) \Bigg/ \left(\sum_{i=1}^{M} p_i\right). \tag{7}$$

In order to objectively evaluate the performance of the color correction method, we calculate the color difference between the reference image and input image, and compare with the color difference between the reference image and the corrected input image. The CIELAB color space is intended to be a perceptually uniform color space, so that equal distance in the color space represents equal perceived differences in appearance. Color difference is defined as the Euclidean distance between two images in this color space

$$\Delta E^*_{ab} = \sqrt{(\Delta L^*)^2 + (\Delta a^*)^2 + (\Delta b^*)^2}, \tag{8}$$

here small $\Delta E^*_{ab}$ means small color difference between images.

In the experiments, multi-view image sequences 'objects2' and 'flamenco1', provided by KDDI Corp., are used as the test sequences. In the proposed method, the threshold $T_1$ is an important parameter deciding precision of color categorizing. Supposing $w(x) = 1 - \frac{1}{1+\mathrm{e}^{-0.5x}}$, Fig. 1(a) shows the curve distribution. It is noted that $x \in [-10, 10]$ is the critical state which maps $w(x)$ to $[0, 1]$. In Fig. 1(b), our statistical analysis shows that Euclidean distance between neighboring pixels in 'flamenco1' image less than 10 accounts for almost 45%. Then combined with Eq. (2b), we consider the color difference is small and weighting function $w$ goes to 1, if only the Euclidean distances is less than 10. Therefore, $T_1 = 20$ is selected in the proposed method.

Table 1 shows the statistical results of dominant color number for different accumulative percentage. From the table, it is noted that if accumulative percentage is less than 0.9, the main dominant colors can be extracted effectively. Therefore, $T_2$ is set to 0.9.

Figures 2(a), 3(a), 2(b), and 3(b) show the reference images and input images of 'objects2' and 'flamenco1' in the first and second viewpoints, respectively. The

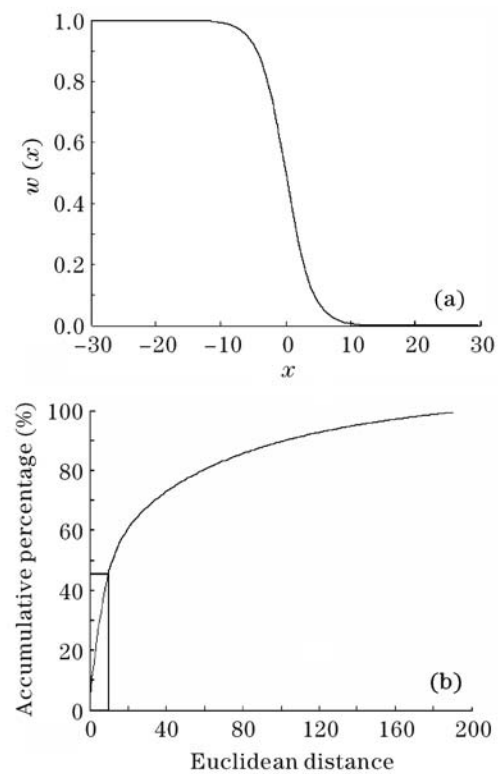


Fig. 1. (a) Curve distribution for $w(x)$; (b) statistical analysis of Euclidean distance.

**Table 1. Statistical Results of Dominant Color Number $M$**

| Image | Accumulative Percentage | | | | | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 11 |
| Objests2 | 0.421 | 0.682 | 0.888 | 0.986 | 0.992 | 1.000 |
| Flamenco1 | 0.865 | 0.951 | 0.969 | 0.984 | 0.995 | 1.000 |

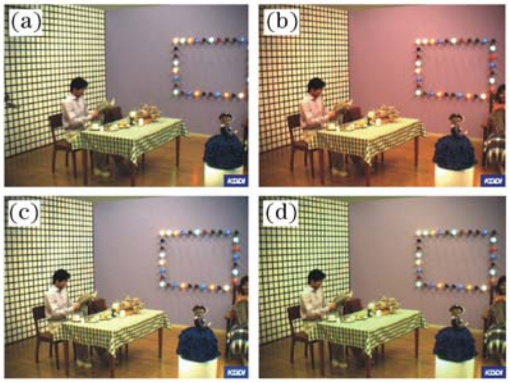


Fig. 2. Color correction results for 'objects2' multi-view images. (a) Reference image; (b) input image; (c) the corrected image with the proposed method; (d) the corrected image with Reinhard's method.

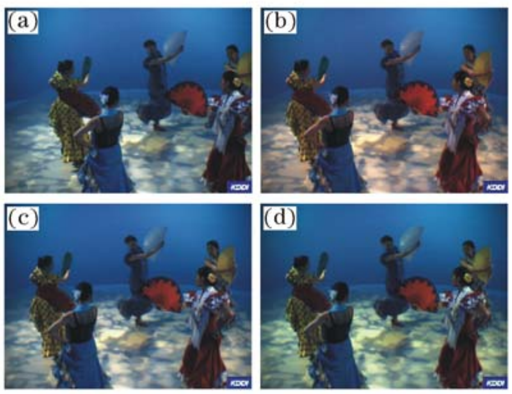


Fig. 3. Color correction results for 'flamenco1' multi-view images. (a) Reference image; (b) input image; (c) the corrected image with the proposed method; (d) the corrected image with Reinhard's method.

corrected images obtained with the proposed method in Figs. 2(c), 3(c) are in full consistent with their reference images in color appearance, while Reinhard's results have slight color difference with their reference images.

Figures 4(a) and (b) show the color difference with respect to the original data without correction, the corrected data obtained with the proposed method and Reinhard's method for successive 50 frames. From the figure, it is obvious that the proposed method achieves the smallest color difference, adequately outperforms the Reinhard's method.

In conclusion, color correction for multi-view image is an important issue in the FVV system. A color correction method based on dominant color extraction for multi-view images is proposed. Experimental results show the effectiveness of the proposed method. The proposed method extracts the dominant color based on a set of fixed color categories, which does not provide robust adaptability to image content. In future work, we

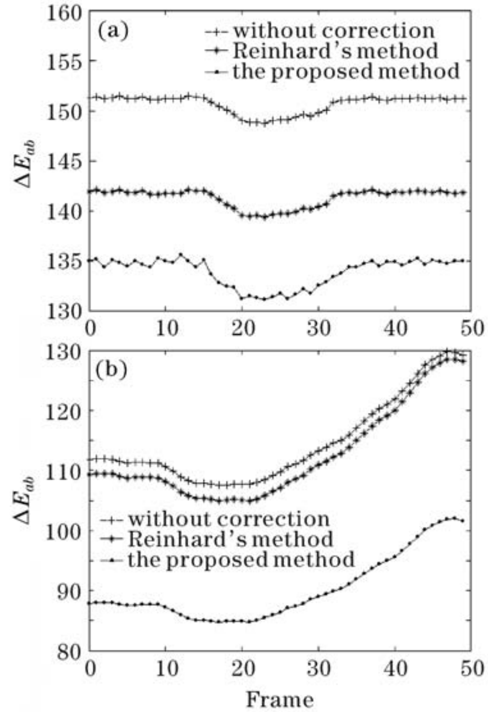


Fig. 4. Color difference for (a) objects2; (b) flamenco1.

will research on intelligent algorithms that automatically understand the image content to find the relation among the scene materials.

This work was supported by the Program for New Century Excellent Talents in University (NCET-06-0537), the National Natural Science Foundation of China (No. 60472100 and 60672073), the Natural Science Foundation of Zhejiang Province (No. Y105577), and the Key Project of Chinese Ministry of Education (No. 206059).
M. Yu is the author to whom the correspondence should be addressed, her e-mail address is yumei@nbu.edu.cn.

## References


1. W. Matusik and H. Pfister, in *Proceeding of SIGGRAPH* **23,** 814 (2004).
2. F. Shao, G. Jiang, M. Yu, and K. Chen, Chin. Opt. Lett. **5,** 28 (2007).
3. H. Zhou, Q. Ren, and W. Li, Laser & Optoelectronics Progress (in Chinese) **41,** (10) 2 (2004).
4. E. Reinhard, M. Ashikhmin, and B. Gooch, IEEE Comput. Graphics and Appl. **21,** (4) 34 (2001).
5. D. L. Ruderman, T. W. Cronin, and C. C. Chiao, J. Opt. Soc. Am. A **15,** 2036 (1998).
6. Y. Chang, S. Saito, and M. Nakajima, IEEE Trans. Image Process. **16,** 329 (2007).
7. S. F. Chang, T. Sikora, and A. Puri, IEEE Trans. Circuits and Systems for Video Technol. **11,** 668 (2001).