ORIGINAL PAPER

Color correction algorithm based on camera characteristics for multi-view video coding

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Received: 23 August 2011 / Revised: 21 February 2012 / Accepted: 9 May 2012 / Published online: 25 May 2012 © Springer-Verlag London Limited 2012

Abstract Various types of multi-view camera systems have been proposed for capturing three dimensional scenes. Yet, color distributions among multi-view images remain inconsistent in most cases, degrading multi-view video coding performance. In this paper, we propose a color correction algorithm based on the camera characteristics to effectively solve such a problem. Initially, we model camera characteristics and estimate their coefficients by means of correspondences between views. To consider occlusion in multi-view images, correspondences are extracted via feature-based matching. During coefficient estimation with nonlinear regression, we remove outliers in the extracted correspondences. Consecutively, we generate lookup tables for each camera using the model and estimated coefficients. Such tables are employed for fast color converting in the final color correction process. The experimental results show that our algorithm enhances coding efficiency with gains of up to 0.9 and 0.8 dB for luminance and chrominance components, respectively. Further, the method also improves subjective viewing quality and reduces color distance between views.

Keywords Camera characteristic curve · Color correction · Color inconsistency problem · Multi-view video coding

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List of symbols

$P_{\rm ref}$	Pixel values of reference
P_{tar}	Pixel values of target cameras
C_{gain}	Coefficients for gain
C_{offset}	Coefficients for offset
C_{gamma}	Coefficients for gamma
2 ^{bitdepth}	The total number of gray levels
У	Pixel value of the reference image in the sample
	set
x	Pixel value of the target image corresponding
	to y
\bar{eta}	Vector consisting of coefficients for each camera
	property
$ar{J}_{ar{e}}$	m \times 3 Jacobian matrix whose <i>i</i> th row equals to
	$\partial(e_i(ar{eta}))/\partialar{eta}$
xe	Estimated value from the camera characteristic
	curve
а	Controlling parameter to distinguish outliers

1 Introduction

The three dimensional (3D) video service has gained massive attention due to its immersive and realistic impression to viewers. In addition, the 3D video can be applied to various applications such as broadcasting systems, games, simulations and educational tools. The contents of the 3D video service commonly consist of two data types: colorimetric and geometric data. To acquire both data, numerous capturing methods have been proposed such as 3D scanners, depth cameras, and multi-view camera systems.

Although 3D scanners [1] and depth cameras [2] can directly measure geometric information, they cannot cover dynamic or outdoor scenes due to technical limitations. The

multi-view images captured at different view positions are widely used for 3D content generation without the above problems [3].

At the early stage in multi-view image study, single-view cameras were mainly adopted [4]. Researchers had to move the camera position around the same object and capture images iteratively. However, dynamic scenes could not be captured in such a way. Thus, researchers had started to increase the number of cameras such that the system can capture scenes at different positions simultaneously.

Despite the advantages, a big obstacle is a huge amount of data. Unfortunately, the amount of information in multiview images increases linearly as the number of cameras. Therefore, the key technical building block of the multiview camera system is compression. The role of efficient coding becomes much more important for 3D systems due to the drastic data increase. Some of the past research and standardization efforts to address this issue include Moving Picture Experts Group(MPEG)-2 Multi-view Video Profile (MVP) [5], MPEG-4 Multiple Auxiliary Component (MAC) [6], and MPEG/JVT Multi-view Video Coding (MVC) [7,8]. Among them, MVC is the latest standard for multi-view image compression, exploiting interview correlation for high performance.

Although multi-view camera systems grant freedom of selecting scenes to be captured, two problems exist: geometrical mismatch and decline of color consistency. The former comes from misalignment of multiple cameras. It causes unnatural viewpoint changes between multiple images and obstructs multi-view image processing. This can be reduced by camera calibration and rectification [9]. The latter is related to inconsistent color distributions among neighboring views due to different camera properties. Noteworthy, color consistency and color constancy are different. Color constancy is a physiological element and a feature of human color perception ensuring that the perceived color remains relatively constant under varying illumination conditions. Such a factor is not directly related to multi-view image processing. This paper only deals with color consistency among views since inter-view correlations and coding efficiency can be affected.

The color distribution of a certain object depends not only on reflectance properties of objects but also on properties of each camera. Even though we capture the same object under the same illumination with cameras of the same kind, the captured color distribution of each multiview image varies. The variations are caused by the different property of charge-coupled device (CCD) or complementary metal-oxide-semiconductor (CMOS) in each camera, jitter of shutter speed and aperture, or the variation of angle between objects and camera.

The color inconsistency problem degrades the coding performance of MVC since MVC exploits interview correlation to increase estimation accuracy. Hence, color correction that reduces the color difference among views is vital for high coding efficiency.

The purpose of color correction for multi-view images is different from that for single-view images. Most of the single-view color correction algorithms focus on recovering an estimate of the scene illumination [10,11], but the main goal of multi-view color correction is to match color distribution among views.

2 Color correction for multi-view images

In order to solve the color inconsistency problem of the multiview images, various color correction algorithms have been researched and proposed. The color correction algorithms for multi-view images can be classified into two categories: with and without pre-processing.

In the algorithms with a pre-process, a known target, such as a color chart, is usually used to calibrate camera's color response property. Ilie and Welch [12] have developed a system aimed at inter-camera color consistency. This method consists of an iterative closed-loop calibration followed by a refinement phase. Joshi et al. [13] have proposed an automated system for calibrating camera arrays to achieve color consistency. The mentioned algorithms utilize a known color chart placed in the scene and adjust camera registers by considering the information of the color chart. However, they only considered a linear color response property even though components of a camera, such as lens and light sensors, have nonlinear properties. These algorithms should require an additional pre-process for capturing the color chart.

For color correction without pre-processing, Fecker et al. [14] have suggested the usage of histogram matching to compensate color inconsistency between views. Chen et al. [15] also have used histogram matching to compute multiplicative and additive variation factors. These methods provide reasonable performance, but depend on occlusion, a newly exposed area according to view position. The occlusion regions make the histogram-based statistical model inaccurate since they are one-sided textures. In order to avoid this, we should calculate the image histogram only on overlapping regions; however, this is impossible without depth information. Therefore, large occlusion regions degrade the performance of such approaches.

Some alternative algorithms using correspondences between neighboring views have been researched [16,17]. Gangyi et al. have proposed a region correspondence-based algorithm. They utilize a mapping relationship built with similar statistical model through Expectation-maximum segmentation, thus the performance depends on the segmentation results. Yamamoto et al. [17] have proposed an energy function with dynamic programing. They have defined an energy function consisting of corresponding and step-by-step energy functions. However, this method is also limited by the manual determination of coefficients in the energy function that can significantly affect the performance. In such a way, the conventional algorithms for color correction are unable to solve the color inconsistency problem effectively.

Therefore, in this paper, we propose a color correction algorithm that considers a nonlinear camera property and the occlusion region without any pre-process. The contribution of this work is that we correct the color distortion on the basis of the camera characteristic curve with an outlier-eliminated nonlinear regression. For camera characteristic curve modeling, the main camera properties, gamma, offset, and gain, are analyzed and expressed as numerical formulas. Using the feature-based matching algorithm, we extract correspondences between reference and target views and estimate coefficients of the camera characteristic curve. Afterward, we generate a lookup table and convert the color distributions of target views. The proposed algorithm is implemented in the MVC software for improving coding performance of multi-view video.

3 Proposed color correction algorithm

3.1 Camera characteristic model

Cameras have various properties that affect color distribution of captured images. Especially in the multi-view camera system, controlling them as we wish is burdensome. This is one of the main reasons why multi-view images have inconsistent color distributions among views. To quantitatively measure color inconsistency and correct it, we model a camera characteristic curve in regard to the colorimetric relationships between reference and target cameras.

The camera characteristic curve represents how much differences are induced when certain intensity light is passed into two cameras. Figure 1 shows the common difference types coming from camera properties. The long-dotted line represents the relation when two cameras have identical characteristics. The other lines stand for relations when two cameras have different camera properties such as gain, offset, and gamma.

Each relation can be expressed as (1).

$$Gain: P_{ref} = C_{gain} \times P_{tar}$$

$$Offset: P_{ref} = P_{tar} + C_{offset}$$

$$Gamma: P_{ref} = \left\{ P_{tar} / (2^{bitdepth} - 1) \right\}^{C_{gamma}} \times (2^{bitdepth} - 1)$$
(1)

where P_{ref} and P_{tar} are pixel values of reference and target cameras. C_{gain} , C_{offset} , and C_{gamma} represent coefficients for



Fig. 1 Relative pixel intensities between target and reference views according to different camera properties: offset, gain, and gamma

each property. 2^{bitdepth} is the total number of gray levels for each color channel, and eight bits are often used for common digital images. $(2^{\text{bitdepth}} - 1)$ term is for normalization of the range of pixel values. We combine three properties into the camera characteristic curve as (2).

$$P_{\text{ref}} = C_{\text{gain}} \left\{ P_{\text{tar}} / (2^{\text{bitdepth}} - 1) \right\}^{C_{\text{gamma}}} \times (2^{\text{bitdepth}} - 1) + C_{\text{offset}}$$
(2)

The coefficients in the camera characteristic curve reflect the inconsistency for each property. The coefficients change according to target and reference images. Thus, estimating the coefficients from captured images is a crucial process

3.2 Correspondence extraction

If we estimate the coefficients from entire parts of the images, the occlusion parts have a bad influence on the coefficients. Therefore, we estimate the coefficients using only pixels with correspondences. Unfortunately, since multi-view images are captured at different positions with different angles, co-located pixels in both images are not guaranteed as correspondences. Through the camera projection model, a certain point can be projected to different positions on the two image planes according to the various factors.

There are various algorithms to extract correspondences between images; most of them mainly employ intensity values as a criterion. However, it is not appropriate for the images having the color inconsistency problem. In this paper, we use the Scale-invariant feature transform (SIFT) algorithm [18]. In particular, SIFT is an algorithm in computer vision used for detecting and describing local features in images. The



Fig. 2 Result of feature-based matching for the *uli* sequence. The *bold lines* are mismatched correspondences

SIFT features, based on the appearance of the object at particular interest points, are local and invariant to image scale and rotation. The SIFT-based matching algorithm does not provide a dense correspondence map but extracts accurate and sparse correspondences.

An image occasionally has saturated pixels that are out of the dynamic range. Since they degrade the accuracy of coefficient estimation, we only regard samples whose pixels are smaller than 250 and larger than five as valid samples. This process reduces the influence of saturation parts and hardware limitations, and improves the performance of coefficient estimation. This threshold values are not for offset compensation. The offset problem is treated in the camera characteristic curve in our algorithm.

Figure 2 shows the results of the SIFT matching for two images of the *uli* sequence. Most of the extracted correspondences (thin lines) are reliable, but some incorrect correspondences (bold lines) also exist. Due to the degradation of coefficient estimation caused by outliers, we use nonlinear regression with an outlier removal process.

3.3 Coefficient estimation

With the correspondences extracted in the previous section, we estimate the coefficients of the camera characteristic curve. Due to the nonlinearity of the curve and outliers, we propose an outlier-removed nonlinear regression based on the Levenberg-Marquardt algorithm [19]. The algorithm has coefficient estimation using regression and outlier removal processes. These are alternately carried out.

First, we define an error function as in (3).

$$e_i(\beta) = y_i - f(x_i, \beta) \tag{3}$$

where y is a pixel value of the reference image in the sample set and x is the pixel value of the target image corresponding to y. The function f, the camera characteristic curve, can be represented by (4), and the vector $\overline{\beta}$ consists of coefficients for each camera property.

$$f(x_i, \bar{\beta}) = \beta_0 \left\{ x_i \left/ (2^{\text{bitdepth}} - 1) \right\}^{\beta_2} \times (2^{\text{bitdepth}} - 1) + \beta_1$$
(4)

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The squared sum of error values is defined as the value *S*, and we reduce *S* by changing the value of vector $\bar{\beta}$.

$$S(\bar{\beta}) = \sum_{m} e_i^2(\bar{\beta}) \tag{5}$$

Starting with an initial guess $\bar{\beta}^0$, the method proceeds iteratively until the error value *S* converges to the minimum value. In this paper, the initial vector is set with {1,0,1}, which is the set of coefficients for the ideal case.

$$\bar{\beta}^{s+1} = \bar{\beta}^s + \delta\bar{\beta} \tag{6}$$

where *s* stands for the number of iteration, and the updating term $\delta \bar{\beta}$ satisfies the augmented normal equations as (7). In (7), \bar{e} is the vector of functions e_i , and the matrix $\bar{J}_{\bar{e}}$ is the m × 3 Jacobian matrix whose *i* th row equals to $\partial(e_i(\bar{\beta}))/\partial \bar{\beta}$.

$$\bar{N}\delta\bar{\beta} = -\bar{J}_{\bar{e}}^T\bar{e} \tag{7}$$

In the augmented normal equation, the matrix, $\bar{J}_{\bar{e}}^T \bar{J}_{\bar{e}}$, is the approximate Hessian and an approximation to the matrix of second-order derivatives. The vector \bar{N} consists of two terms for fast speed and the assurance of convergence. Both are controlled by damping parameter λ as shown in (8).

$$\bar{N} = \left(\bar{J}_{\bar{e}}^T \bar{J}_{\bar{e}} + \lambda \cdot \operatorname{diag}\left(\bar{J}_{\bar{e}}^T \bar{J}_{\bar{e}}\right)\right)$$
$$\delta\bar{\beta} = -\left(\bar{J}_{\bar{e}}^T \bar{J}_{\bar{e}} + \lambda \cdot \operatorname{diag}\left(\bar{J}_{\bar{e}}^T \bar{J}_{\bar{e}}\right)\right)^{-1} \bar{J}_{\bar{e}}^T \bar{e}$$
(8)

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If the damping parameter is set to a large value, matrix N is nearly diagonal and the updating step is near the steepest descent direction, guaranteeing that the output value converges to the minimum; however, such a process is time-consuming. While the damping term has a small value, the process approximates the exact quadratic step appropriate for a fully linear problem. This parameter is automatically adjusted during iteration. Initially, we set λ with λ_0 and compute the residual sum of squares $S(\bar{\beta})$ after one step from the starting point with the damping factor of $\lambda = \lambda_0$. Secondly, we set λ with λ/v where v is larger than zero. If both are worse than the initial point, then the damping is increased by successive multiplication by v until a better point is found. This process is repeated until residue value S converges to the minimum value.

After regression, the curve having the minimum residue value is obtained, yet this result can be influenced by outliers coming from the inaccurate matching process as shown in Fig. 2. For outlier removal, we distinguish valid samples from the initial samples. Overall process is shown in Fig. 3. We discard samples located outside doubled h and discard them from the sample set. The range of h is calculated by (9)

$$h = a \sqrt{\frac{1}{m} \sum_{m} (x_i - x_e)^2}$$
 (9)



Fig. 3 Outlier removal process: a coefficient estimation with the initial samples, b finding valid sample region, and c coefficient estimation with valid samples





where x_e is an estimated value from the camera characteristic curve, and the value *a* is a controlling parameter to distinguish outliers from the sample set that defines a permissible range of outliers. Empirically determined, we use a constant value 1.5 for *a*. After outlier removal, we apply the nonlinear regression process again. This cycle consists of regression, and outlier removal is repeated until all remaining samples are in the valid sample region. This process is individually performed for each channel because a camera has individual sensors for each channel, containing independent gain, gamma, and offset values.

Figure 4 shows the examples of the nonlinear regression with and without outlier removal. While several outliers bend the fitting curve up in Fig. 4a, the well-fitted curve can be obtained as shown in Fig. 4b.

Figure 5 demonstrates the calculated camera characteristic curve and the initial samples of the *uli* sequence. In spite of serious outliers, the camera characteristic curves are well fitted without their influences. Table 1 shows the calculated coefficients of the camera characteristic model. The processing time for coefficient estimation including SIFT matching depends on various attributes such as image size, the number of samples, and outliers. On Intel Xeon X5450 processor at 3.0 GHz, 5–15 s are taken. The estimated coefficients are valid until the camera settings change. Therefore, we do not need to conduct this process for every frame.

3.4 Lookup table and conversion

We convert pixel values of the target view by using the camera characteristic curve and estimated coefficients. In order to convert pixel values for one frame, 0.67s is necessary for XGA images. For faster execution, we generate lookup tables that possess all intensity values in the dynamic range and their converting values by using (10).

$$Value_{lookup_i} = \beta_0 \left\{ i / (2^{bitdepth} - 1) \right\}^{\beta_2} \times (2^{bitdepth} - 1) + \beta_1$$
(10)

By changing *i* from 0 to $2^{\text{bitdepth}} - 1$, the corrected values Value_{lookup_i} are calculated and saved in the lookup table. The table reduces the time required to convert pixel values from 0.67 to 0.45 s. Figure 6 demonstrates the result of color correction.

4 Experimental results and analysis

The two experiments were carried out to evaluate the performance of the proposed algorithm. The first experiment assesses the performance of color correction in itself, while the second evaluates the coding performance using our algorithm as a pre-processing method. **Fig. 5** Camera characteristic curves for view 3 of the *uli* sequence (reference view—view 4): **a** *red*, **b** *blue*, and **c** *green* channels



 Table 1
 Estimated coefficients of the camera characteristic curve

Coefficient	Red	Green	Blue
Gain	1.01	0.94	0.94
Offset	25.04	-1.10	21.85
Gamma	1.32	1.06	1.37



Fig. 6 Original view 4 and view 3 of the *uli* sequence, and color-corrected view 3

4.1 Color consistency

First, we tested on the *race, flamenco, breakdancers*, and *ballroom* sequences, which are standard multi-view sequences of MPEG. We selected sixty temporal frames of five views for each sequence and implemented two conventional algorithms: histogram matching (HM) [14] and energy function (EF) [17] for comparison. In [14], Fecker et al. mentioned that global disparity compensation does not ensure improvement of coding efficiency so they excluded it in their experiments. Therefore, we also do not apply the method in

our procedure. We used the same and constant parameters Yamamoto et al. have used in [17].

Figures 7 and 8 show the original and color-corrected sequences. Since each sequence has five views with different conditions, showing all sequences at once is not practical due to limited space. Therefore, we only demonstrate the *race* and *flamenco* sequences in this paper. While finding differences in the *race* sequence is problematic due to small and similar occlusions, the *flamenco* sequence shows distinct results for each algorithm.

For close observation, we enlarged some parts (red boxes in Fig. 8) and attached them in Figs. 9 and 10 in view order. While the color distribution of the 1st, 2nd, and 4th views of HM is noticeably different than the reference view (view 3) in Fig. 9b, EF, and our algorithm show stable results without occlusion problem. However EF has another problem in areas of smooth gray levels as shown in Fig. 10c. The ridges look like false contouring effects, and gray scale inversion can even appear. Such visual artifacts arise when some acquired samples are inaccurate or the samples do not increase step-by-step, since the two energy functions of [17] conflict. Although the constant weighting value used in EF controls this confliction, it is hard to define the constant value properly for various images. This phenomenon can cause low coding efficiency due to the increase in high frequency components. Contrarily, the proposed algorithm corrects color distributions well and maintains image smoothness.

Fig. 7 Original and color-corrected *race* sequences: a original, b HM, c EF, and d proposed

Fig. 8 Original and color-corrected *flamenco* sequences: a original, b HM, c EF, and d proposed

Fig. 9 Enlarged complex parts of the *flamenco* sequence: a original, b HM, c EF, and d proposed











Fig. 11 Results of the subjective quality assessment

Thirteen observers participated in the subjective quality assessment. During the assessment, the original and colorcorrected test sequences were displayed in a random fashion. Each view of the sequences was displayed in the view order at a one-second interval. The observers were asked to give scores according to the ITU-R BT.500-11 recommendations [22]. The test results are demonstrated in Fig. 11. While the performances of HM and EF depend on test sequences, the proposed algorithm shows stable and reliable results. Although the proposed algorithm ranked low on the *breakdancers* sequence, there was little difference in the viewing quality among the algorithms. Other than the *breakdancers* sequence, the proposed algorithm was given the highest rating.

For quantitative analysis, we captured the test images with the GretagMacbeth ColorCheckerTM by using a multi-view camera system, which consists of five HD color cameras (Canon XL-H1). We used two camera configurations: identical and automatic. In the identical configuration (C_{iden}), all cameras are equivalently set up, and the settings are fixed during capturing. The automatic configuration (C_{auto}), which is developed by Canon, automatically controls several camera options such as white balance, shutter speed, and aperture ratio, according to scenes. In C_{auto} , the settings can be changed on the fly. Figure 12a and b demonstrate the captured images with C_{iden} and C_{auto} , respectively.

Figure 12c–e are the results of HM, EF, and our algorithms on the multi-view images captured with C_{iden} . The background in Fig. 12c becomes blue as the red grid board appears in view 4 and view 5, which is a typical occlusion problem.

In order to objectively measure color consistency, we extracted color samples of the color charts from all views. Further, we calculated mean square error (MSE) values and Euclidean distances (ED) in the CIELab color space. CIELab is a standardized linear color space that makes in the CIELab space linearly related to human judgments of color differences. The CIELab colors are described by 'L' for lightness, 'a' for green to magenta, and 'b' for blue and yellow. We calculate ED by

$$ED = \frac{1}{m} \sum_{i=1}^{m} \sqrt{(L_i - L_{ref_i})^2 + (a_i - a_{ref_i})^2 + (b_i - b_{ref_i})^2}$$
(11)

where m is the total number of samples in the color chart. The subscript *Ref* means the sample value of the reference image, view 3. Table 2 summarizes the results, and Fig. 13 displays each ED in a diagram.

While the performance of HM depends on occlusion parts, EF and our method show the stable and reliable results. However, the coding efficiencies are different due to EF's weakness in smooth gray level areas.

4.2 Coding performance

We conducted experiments on the MPEG standard sequences in order to verify the coding efficiency. We additionally

Fig. 12 Captured test images and the results of color correction: **a** *C*_{iden}, **b** *C*_{auto}, **c** HM, **d** EF, and **e** proposed



 Table 2 Mean square errors and Euclidean distances in the CIELab color space

Method		View 1	View 2	View 4	View 5
Ciden	MSE (L)	1.38	0.52	1.06	1.18
	MSE (a)	0.23	0.22	0.28	0.32
	MSE (b)	0.29	0.19	0.22	0.21
	ED	1.43	0.60	1.12	1.24
$C_{\rm auto}$	MSE (L)	0.51	0.14	0.22	0.41
	MSE (a)	0.32	0.16	0.26	0.24
	MSE (b)	0.23	0.16	0.69	0.20
	ED	0.64	0.26	0.77	0.52
HM	MSE (L)	0.41	0.48	1.25	1.46
	MSE (a)	0.44	0.20	0.04	0.50
	MSE (b)	0.31	0.39	0.95	0.96
	ED	0.67	0.65	1.62	1.82
EF	MSE (L)	0.30	0.22	0.24	0.28
	MSE (a)	0.28	0.28	0.28	0.27
	MSE (b)	0.25	0.16	0.21	0.22
	ED	0.48	0.39	0.42	0.44
Proposed	MSE (L)	0.28	0.22	0.22	0.25
	MSE (a)	0.28	0.26	0.27	0.26
	MSE (b)	0.18	0.18	0.18	0.27
	ED	0.43	0.39	0.39	0.45

compared our algorithm with illumination compensation (IC), implemented in the Joint Multi-view Video Model (JMVM) reference software [20], as well as HM and EF. All algorithms were implemented on JMVM 6.0, and each sequence was coded, in the YUV color domain with quantization parameters (QP) of 22, 27, 32, and 37.



Fig. 13 Quantitative comparison

Figures 14, 15, 16 and 17 are the rate distortion curves for each sequence. Tables 3 and 4 summarize the comparison of the coding performance. The PSNR difference or bit saving was measured using the Bjontegaard metric [21]. HM and EF show better results in some test sequences, although wide variations exist according to sequences and color channels. The performances of HM and EF are drastically degraded especially when the sequence had large occlusion or gradation regions, which can be shown in the results of the *flamenco* sequence.

The proposed algorithm exhibited the best coding efficiency and stability over all test sequences. The luminance BDPSNR gains ranged from about 0.2 to 0.96 dB when compressing the original data with the JMVM and illumination compensation not applied.

5 Conclusion

In this paper, we proposed a color correction algorithm based on the camera characteristic curve for multi-view video

- - Orginal

- IC

-×--- HM

•-· EF

1500

- Proposed

2000

v

1000

42

41

40

36

35

0

500



Fig. 14 Rate distortion curves for the *race* sequence



Fig. 15 Rate distortion curves for the *flamenco* sequence



Fig. 16 Rate distortion curves for the breakdancers sequence



Fig. 17 Rate distortion curves for the *ballroom* sequence





Table 3 Comparison of BDPSNR for the illumination compensation, histogram matching, energy function, and proposed method

BDPSNR (dB)	Y				U				V			
	IC	HM	EF	Proposed	IC	HM	EF	Proposed	IC	HM	EF	Proposed
race	0.48	0.39	0.32	0.96	0.24	0.55	0.47	0.83	0.22	0.33	0.15	0.83
flamenco	0.15	0.08	-0.40	0.58	0.09	0.02	0.03	0.55	0.07	-0.05	-0.46	0.58
breakdancers	0.12	0.10	0.18	0.40	-0.02	-0.11	-0.37	0.24	0.01	0.03	-0.12	0.33
ballroom	0.09	0.05	0.24	0.20	0.04	0.05	0.06	0.14	0.03	-0.02	-0.04	0.05

Table 4 Comparison of BDBR for illumination compensation, histogram matching, energy function, and proposed method

BDBR (%)	Y				U				V			
	IC	HM	EF	Proposed	IC	HM	EF	Proposed	IC	HM	EF	Proposed
race	-10.82	-8.67	-7.34	-20.57	-7.36	-17.18	-14.95	-26.52	-7.44	-11.55	-5.32	-27.13
flamenco	-3.18	-1.49	10.62	-11.63	-2.92	-0.46	-0.99	-17.26	-2.51	2.00	20.14	-19.41
breakdancers	-5.87	-4.57	-7.94	-16.78	1.24	7.76	32.81	-13.97	-0.69	-1.73	8.87	-18.68
ballroom	-2.20	-1.29	-6.13	-5.08	-1.63	-1.80	-2.39	-5.56	-1.09	1.04	1.73	-1.90

coding. In order to model camera characteristics, the camera properties were analyzed and expressed as numerical formulas. We extracted sparse and accurate correspondences between views and estimate the appropriate coefficients of the camera characteristic curve with outlier-removed non-linear regression. Finally, we generated lookup tables and corrected the color distribution of target views. In the experimental results, the proposed algorithm shows good subjective qualities and reduces Euclidean distances in the CIELab color space. Unlike other algorithms, our method is robust to occlusion and various textured regions. To summarize, the proposed method achieved 0.54 dB PSNR gain or 13.4 % bit saving on average compared to the conventional method.

Acknowledgments This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MEST) (No. 2011-0030822).

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