Color Matching of Image Sequences with Combined Gamma and Linear Corrections

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ABSTRACT

This paper addresses the problem of color and luminance compensation for sequences of overlapping images where the source images have very different colors and luminance. We apply the method for panoramic image construction on mobile phones. A simple approach is proposed that minimizes both the color differences of neighboring images and the overall color correction over the whole sequence. We compare several combinations of gamma correction and linear adjustment over different color representations, and select the method with best results: use $YCbCr$ and apply gamma correction for the luminance component and linear correction for the chrominance components.

Categories and Subject Descriptors

I [**Computing Methodologies**]: Computer GraphicsPicture/Image Generation Graphics Utilities; I [**Computing Methodologies**]: Image Processing and Computer Vision-Application

General Terms

Algorithms, experimentation

Keywords

Mobile panorama, color correction, color and luminance compensation, color blending, gamma correction, mobile image processing, mobile computational photography

1. INTRODUCTION

Practically all modern high-end mobile phones come with a high-resolution camera and relatively lot of processing power, enabling many interesting visual applications such as mobile image recognition and display of related information [6] and mobile panoramic imaging [9].

During panorama construction, a sequence of source images is captured by rotating a camera so it sees different parts of a scene. As the image parameters such as exposure and white balance are recalculated for each input image, changes in illumination in different parts of the scene lead to different exposure levels in adjacent images, and objects of different colors in different parts of the scene affect the white-balance settings, causing the same objects to appear different, either brighter or darker, or even with a different apparent color, in neighboring images. If there is no additional color and luminance processing, artifacts in the overlapping areas of the images may be created in the final panoramic image, and stages of image stitching that assume that the same object has the same color values may fail. Figure 1 shows an example with eight source images with very different colors and luminance. The composite image shown on the top is created by stitching the source images together. The result shows that the color differences and seams between source images can be seen very clearly in the composite image. It is necessary to perform color and luminance compensation for the source images to reduce these artifacts before stitching them together.

Figure 1: Composite image created with source images of differing colors and luminance.

Even if in a later stage a more complex blending algorithm such as Poisson blending [10] is used, there are several reasons why a quick color matching is a useful early step on the panorama stitching pipeline. For example, when calculating a seam between neighboring images most methods try to find a seam over pixels that are similar in both images. That way the seam does not cut through any moving object (such as a car or a person) but the seam goes through a common background. However, if the colors differ, the assumptions for finding a good seam do not hold, resulting in low-quality seams, which may even cut through an object that is only present in one of the images [11]. Color correction can also improve the quality of image blending. Even though Poisson blending can be used to smoothen the differences between neighboring images in an image sequence, it can do a better job the more similar the images are to begin with. Also, iterative Poisson solvers converge faster

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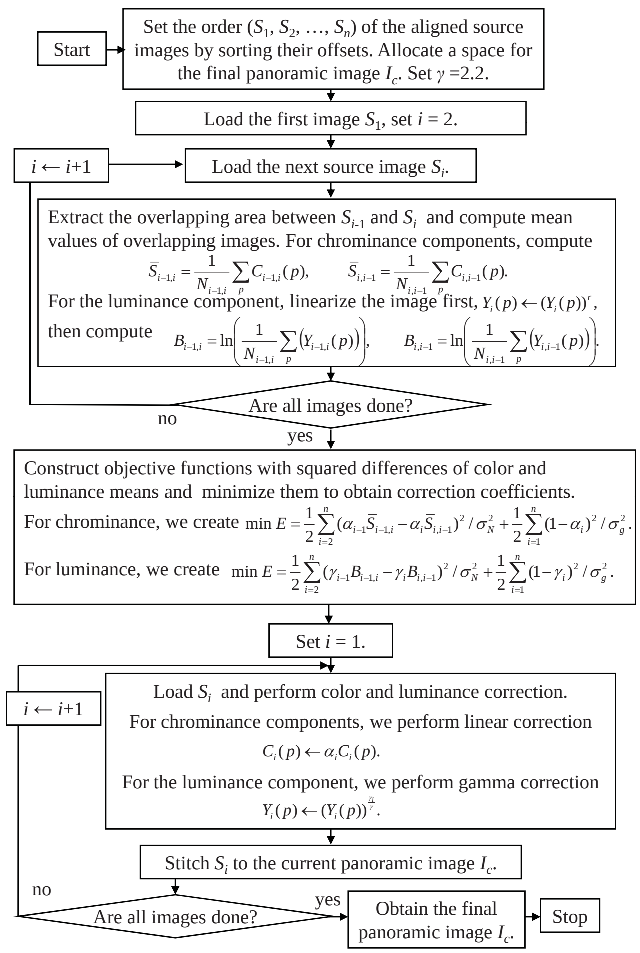


Figure 2: Work flow of panorama stitching with color and luminance correction.

if the colors of the overlapping images match well, and our color matching approach runs much faster than any Poisson solver. For these reasons it makes sense to add a relatively cheap color matching stage after image registration and before image blending in applications such as panoramic image generation.

1.1 Related Work

There are several approaches for color and luminance compensation for image sequences. Some of them [1, 3, 4, 7, 12] are simple and fast, however, with those simple methods accuracy of color and luminance correction is not high. Others [2, 5] can provide more accurate correction, however, accurate pixel correspondences and more computation in the correction process are needed.

Tian et al. [7] propose a simple linear model that computes a scale factor that matches the averages of each channel over the overlap area in the $sRGB$ color space. The benefit of the method is that no accurate pixel correspondences are required. There are some problems in this approach. Pixels saturate very easily during color correction, especially as the corrections are accumulated over a long image sequence; averages of the gamma-corrected $sRGB$ pixel values do not correspond to gamma-corrected averages of linear amounts of light, resulting in correction errors; and the final result depends on the order of the source images during color and luminance correction, especially on the first image which remains unchanged during color correction.

Ha et al. [3] perform a linear correction that is otherwise quite similar to Tian et al. [7], except that they operate in the $YCbCr$ color space. The same problems as with the linear model still exist and need to be solved.

Xiong and Pulli [8] perform color correction in the linearized RGB color space instead of the gamma-corrected $sRGB$ color space so the color averages they calculate are more physically correct. A local linear correction coefficient for each source image is computed using the means of colors in the overlapping areas of adjacent source images in the linearized RGB color space. In order to reduce the magnitude of the cumulative corrections and reduce saturation risk, they calculate a global adjustment factor to minimize color changes across the whole image sequence. The color correction for each source image is performed by combining the local and global correction coefficients. To make the color correction processing be roughly independent of the source image order, they look for an image with the best color and luminance in the image sequence and the color correction process starts with this image. Since only color means are matched during the color correction, no accurate pixel correspondences are needed.

Meunier and Borgmann [4] only consider the luminance channel to match exposures. However, instead of using the gamma-corrected values, they undo the gamma correction and calculate the averages in linear intensity. Instead of separately calculating pairwise correction factors, they formulate a global error equation that solves all the factors simultaneously. In this way, the cumulative errors caused by the color correction process in [7, 3] can be avoided. Brown and Lowe [1] use almost the same method as Meunier and Borgmann, except that they operate in nonlinear gamma-corrected intensity space.

Pham and Pringle [5] perform color and luminance correction using polynomial mapping functions. Pixel pairs in the overlapping area of two images are used to compute the parameters of the polynomial mapping function. The approach can perform accurate color correction. However, since exact correspondences of pixels in both images are needed, the approach is sensitive to spatial alignment errors. And even if the backgrounds of images are perfectly aligned, some foreground objects may differ, due to object motion, or apparent motion due to parallax if the camera was also translated and not just rotated around its optical axis. Our driving application is taking panoramas of real scenes, with moving people, and performing the capture with a handheld camera rather than one on a tripod, we need more robust methods that are relatively insensitive to small registration errors. According to our experiments even simple polynomial models (offset and scale) require accurate pixel correspondences for good results. Furthermore, a non-linear minimization required for solving a polynomial model is more complex than the approaches that solve a linear or gamma correction for the color and / or luminance components.

Zhang et al. [12] propose to construct a mapping function between the color histograms in the overlapping area of the source images. A color correction is performed using the mapping function for the adjacent image. Since no

Figure 3: Result of local linear color correction.

exact pixel correspondences are needed, the method is not sensitive to the quality of spatial alignment. However, the accuracy of color correction is not as good as with polynomial correction.

1.2 Our Work

We are interested in developing a simple color and luminance compensation approach for panorama stitching to create high-resolution and high-quality panoramic images on mobile phones. We want to match the exposure levels of different auto-exposed images. We also want to match the color and luminance balances which often differ from image to image depending on the overall image content and the auto-white-balance algorithm used. We compute correction coefficients using a global optimization process to adjust colors and luminance in the whole image sequence to avoid cumulative errors and make the correction process be independent of the order of source images. We perform gamma correction for the luminance component of a source image to avoid pixel saturation problems and obtain good transitions between the source images. We perform linear correction for the color components for the source image in the linearized color space instead of the gamma-corrected $sRGB$ color space, so that we can obtain good quality of color correction. In order to make the approach more robust to the quality of spatial alignment and obtain good performance, we match corrected means of luminance and colors in the overlapping areas of source images. There are some important advantages in our approach. As opposed to approaches based on linear color adjustments, our method does not saturate pixels values. As opposed to approaches using polynomial function fitting, our method does not require exact pixel correspondences in the overlapping areas. Methods that require exact pixel correspondences are susceptible to registration errors, whereas our approach works robustly even if images are imperfectly registered. We have implemented this system as a part of a panorama image capture and creation system that runs on a mobile phone.

1.3 Main Contributions of this Work

We propose a simple approach to address color and luminance compensation for long image sequences with source images in very different colors and luminance that (i) avoids pixel overflow problems during the color and luminance correction process; (ii) balances colors and luminance of source images in the whole image sequence globally and makes the correction process be independent of the source image order; (iii) compares color and luminance correction results with other approaches to demonstrate advantages of the proposed approach. The color and luminance correction approach is integrated with panoramic image stitching to create high-resolution and high-quality panoramic images on mobile phones.

2. DETAILS OF THE APPROACH

2.1 Overview

Figure 2 shows the work flow of panorama stitching with color and luminance compensation. The procedure starts with setting the stitching order for the source images in the image sequence by sorting their offsets obtained using a motion tracking process during image capturing and allocating a space for the final panoramic image. Then the overlapping areas between adjacent images are extracted. For chrominance components, we compute mean color values of the overlapping images to obtain linear correction coefficients. For the luminance component, we compute a logarithmic mean in the linearized luminance space to obtain a gamma-correction coefficient. Next, an objective function can be constructed with squared differences between the corrected mean values of corresponding overlapping images. It is a function of all gamma coefficients and linear correction coefficients. We minimize the objective function over the image sequence to obtain these coefficients. Gamma correction for the luminance component and linear correction for chrominance components of each source image can be performed with the corresponding coefficients. Finally, a panoramic image can be created by stitching the color- and luminance-corrected source images together. In the following sections, the details of the approach will be described.

2.2 Problem Expression

As described in the previous section, there are several problems in linear color correction: pixels are very easily saturated during color correction processing, there are cumulative errors in color correction for image sequences, and the order of source images in the color correction process and the quality of the first image affect the final result. Figure 3 shows an example result created by a linear color-correction approach [7]. From the result we can see that pixels in many areas such as the sky and the road are saturated and details in these areas are lost. Due to the cumulative errors, the panoramic image becomes brighter from left to right. Since the first image remains unchanged, bad colors in the first image twist the colors of the whole sequence. Since the color correction is performed locally, color transitions in the panoramic image are not good.

We want to create a color and luminance compensation approach which avoids pixel saturation problems, removes cumulative errors, makes the correction process be indepen-

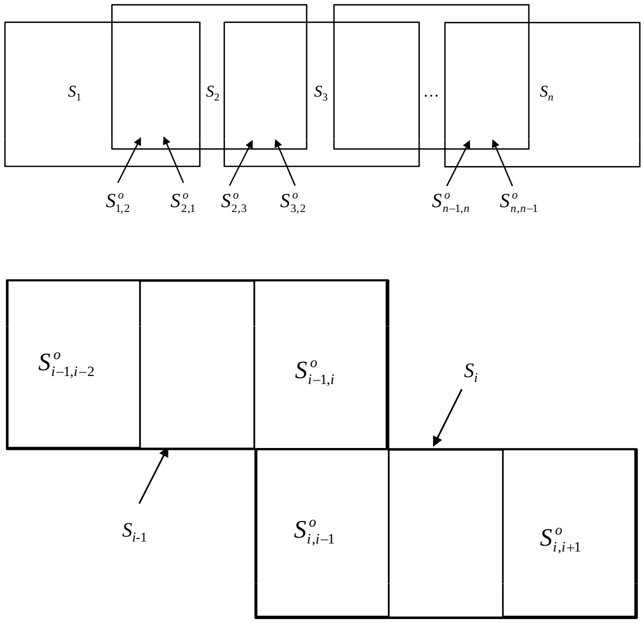


Figure 4: Overlapping source images in an image sequence.

dent of the correction order of the source images, and adjusts color and luminance globally over the whole image sequence. In order to do this, we perform color and luminance compensation for the source images based on the combination of gamma-correction for luminance and linear correction for chrominance and use an optimization process to obtain the correction coefficients globally in the whole image sequence. We compare different implementations and select the one with the best results and performance.

Figure 4 illustrates the notation used in the following sections. Figure 4 (top) shows an image sequence S_1, S_2, S_3, $\ldots$, S_n where each adjacent image overlaps. We denote the overlapping areas with denoted as $S^o_{1,2}$, $S^o_{2,1}$, $S^o_{2,3}$, $S^o_{3,2}$, $\ldots$, $S^o_{n-1,n}$, $S^o_{n,n-1}$, where the first image index tells which image is a part of, and the second gives the index of the neighbor, as indicated in Figure 4 (bottom).

2.3 Matching Means of Gamma-Corrected Pixels in sRGB

In our first attempt we use gamma correction to match colors of overlapping images areas in the *sRGB* color space. In our objective function we apply gamma correction to each pixel separately.

Suppose $C_{i-1,i}(p)$ is the color value of pixel p in image $S^o_{i-1,i}$ and $C_{i,i-1}(p)$ is the color value of the corresponding pixel p in image $S^o_{i,i-1}$. After gamma correction, we hope that

$$\frac{1}{N_{i-1,i}}\sum_p C_{i-1,i}(p)^{\gamma_{i-1}} = \frac{1}{N_{i-1,i}}\sum_p C_{i,i-1}(p)^{\gamma_i}, \qquad (1)$$

where γ_{i-1} and γ_i are gamma-correction coefficients for images $i-1$ and i, and $N_{i-1,i}$ is the number of pixels in the overlap area.

In order to obtain the gamma-correction coefficients γ_i ($i = 1, 2, \ldots, n$), we define an error function over all source images in the image sequence. The error function is the sum of squared differences of gamma-corrected colors between all corresponding pixels in overlapping areas. Denoting

$$U_{i,j} = \frac{1}{N_{i,j}}\sum_p C_{i,j}(p)^{\gamma_i}, \qquad (2)$$

we get

$$E_1 = \frac{1}{2}\sum_{i=2}^{n}\left(U_{i-1,i} - U_{i,i-1}\right)^2. \qquad (3)$$

Since $\gamma_i = 0, (i = 1, 2, \ldots, n)$ is an optimal solution to the problem, we add a prior term to keep the gamma coefficients close to unity. We also consider normalization between color and the gamma-correction coefficient errors. The error function becomes

$$\min E_1 = \frac{1}{2}\left(\sum_{i=2}^{n}(U_{i-1,i} - U_{i,i-1})^2/\sigma_N^2 + \sum_{i=1}^{n}(1-\gamma_i)^2/\sigma_g^2\right), \qquad (4)$$

where σ_N and σ_g are the standard deviations of the normalized color and luminance errors and gamma coefficients. We choose values $\sigma_N = 2.0/255$ and $\sigma_g = 0.5/255$ (when the image value range is normalized to $[0, 1]$).

After minimizing Equation 4, we obtain the optimal gamma-correction coefficients and perform gamma correction for all source images

$$C_i(p) \leftarrow C_i(p)^{\gamma_i}, (i = 1, 2, \ldots, n). \qquad (5)$$

Note that the color correction is performed for the whole image instead of only the overlapping areas.

Figure 5 shows a result obtained by gamma-correcting the source images shown in Figure 1. By comparing to the result obtained by the linear model shown in Figure 3, we can see that the color saturation problem is avoided and the details of the related areas are kept; the colors are adjusted in the whole image sequence including the first image, and there are no cumulative errors caused by the color-correction process. The problems in the linear model are solved and better results are obtained. However, since the gamma coefficients are obtained by solving the highly nonlinear Equation 4, a time-consuming iterative procedure is needed for the minimization process.

2.4 Matching Gamma-Corrected Means in sRGB

To simplify the computation, make the algorithm robust to spatial alignment errors, and speed up the algorithm, we first calculate the means over the overlapping areas and apply the gamma correction to them. Equation 1 becomes

$$\left(\frac{1}{N_{i-1,i}}\sum_p C_{i-1,i}(p)\right)^{\gamma_{i-1}} = \left(\frac{1}{N_{i-1,i}}\sum_p C_{i,i-1}(p)\right)^{\gamma_i}. \qquad (6)$$

Applying logarithm to both sides and denoting

$$B_{i,j} = \ln\left(\frac{1}{N_{i,j}}\sum_p C_{i,j}(p)\right), \qquad (7)$$

Equation 6 becomes

$$\gamma_{i-1}B_{i-1,i} = \gamma_i B_{i,i-1}. \qquad (8)$$

Figure 5: Result of gamma color correction in the $sRGB$ color space.

Figure 6: Result of gamma color correction with mean color matching in the $sRGB$ color space

Squaring the errors we get

$$E_2 = \frac{1}{2}\sum_{i=2}^{n}\left(\gamma_{i-1}B_{i-1,i} - \gamma_i B_{i,i-1}\right)^2. \quad (9)$$

Biasing the gamma coefficients towards unity, that is, no change, and normalizing between color and the gamma coefficient errors, the error function becomes

$$\min E_2 = \frac{1}{2}\left(\sum_{i=2}^{n}\left(\gamma_{i-1}B_{i-1,i} - \gamma_i B_{i,i-1}\right)^2/\sigma_N^2 + \sum_{i=1}^{n}(1-\gamma_i)^2/\sigma_g^2\right). \quad (10)$$

This is a quadratic objective function in the gamma coefficients $\gamma_i, (i = 1, 2, \ldots, n)$ which can be solved in a closed form by setting the derivatives to zero.

$$\begin{cases} \frac{\partial E_2}{\partial \gamma_1} = \left(\frac{B_{1,2}^2}{\sigma_N^2} + \frac{1}{\sigma_g^2}\right)\gamma_1 - \frac{B_{2,1}B_{1,2}}{\sigma_N^2}\gamma_2 - \frac{1}{\sigma_g^2} \\ \frac{\partial E_2}{\partial \gamma_n} = -\frac{B_{n-1,n}B_{n,n-1}}{\sigma_N^2}\gamma_{n-1} + \left(\frac{B_{n,n-1}^2}{\sigma_N^2} + \frac{1}{\sigma_g^2}\right)\gamma_n - \frac{1}{\sigma_g^2} \\ \frac{\partial E_2}{\partial \gamma_i} = -\frac{1}{\sigma_N^2}B_{i-1,i}B_{i,i-1}\gamma_{i-1} \\ \left(\frac{B_{i,i-1}^2}{\sigma_N^2} + \frac{B_{i,i+1}^2}{\sigma_N^2} + \frac{1}{\sigma_g^2}\right)\gamma_i - \frac{1}{\sigma_N^2}B_{i+1,i}B_{i,i+1}\gamma_{i+1} - \frac{1}{\sigma_g^2} \\ (i = 2, 3, \ldots, n-1). \end{cases} \quad (11)$$

By setting $\frac{\partial E_2}{\partial \gamma_i} = 0$, we get a tri-diagonal system of linear equations that can be easily solved using LU decomposition.

Solving Equation 11 is much faster than solving Equation 4. We will perform comparison Section 3.

After obtaining the optimal gamma correction coefficients, we perform color correction with Equation 5 for all source images in the image sequence. Figure 6 shows the result obtained by the gamma color correction with corrected color mean matching in the $sRGB$ color space for the images in Figure 1. We can see that there are no color saturation and cumulative error problems. The color transitions are smoothed in the whole panoramic image and the colors are more natural than the results in Figures 1.

2.5 Combining Gamma and Linear Corrections

To perform luminance and chrominance compensation respectively and obtain good correction results, we separate luminance and chrominance components for source images and perform gamma correction for the luminance component and linear correction for the chrominance components. Instead of using the RGB color space, we perform the corrections in the $YCbCr$ color space.

We first perform linearization for the luminance channel,

$$Y_i(p) \leftarrow Y_i(p)^{\gamma}, (i = 1, 2, \ldots, n). \quad (12)$$

where $Y_i(p)$ is the luminance value at pixel p in source image S_i and $\gamma = 2.2$ is a gamma coefficient.

Then, we process the luminance channel Y using Equations 10 and 11 to obtain gamma coefficients γ_i and apply them to the images (and undo the linearization of Equation 12):

$$Y_i(p) \leftarrow Y_i(p)^{\frac{\gamma_i}{\gamma}}, (i = 1, 2, \ldots, n). \quad (13)$$

For chrominance components Cb and Cr, we use the following way to obtain linear correction coefficients.

We first compute color means $\overline{S_{i-1}}$ and $\overline{S_i}$ in the overlapping area with

$$\overline{S_{i,j}} = \frac{1}{N_{i,j}}\sum_{p} C_{i,j}(p). \quad (14)$$

Then, we construct an error function with corrected color mean matching:

$$\min E_3 = \frac{1}{2}\left(\sum_{i=2}^{n}(\alpha_{i-1}\overline{S_{i-1,i}} - \alpha_i\overline{S_{i,i-1}})^2/\sigma_N^2 + \sum_{i=1}^{n}(1-\alpha_i)^2/\sigma_g^2\right). \quad (15)$$

Like Equation 4, it is a quadratic function in the color correction coefficients α_i which can be solved in a closed form.

Finally, we can perform linear correction for the chromi-

Figure 7: Result of gamma correction for luminance and linear correction for chrominance components

nance components for all source images

$$C_i(p) \leftarrow \alpha_i C_i(p), (i = 1, 2, \ldots, n). \quad (16)$$

where $C_i(p)$ ($C \in \{Cb, Cr\}$) is the color value at pixel p in image S_i.

Figure 7 shows the result obtained by this approach in the $YCbCr$ color space for the source images shown in Figure 1. By comparing with the previous results we can see that the color transitions in the whole panoramic image are more smooth and the colors are more natural.

3. RESULT ANALYSIS

The color and luminance compensation approach is integrated into a panorama stitching procedure running on a camera phone. It has been tested with several image sequences and it produces good results with long image sequences with source images that have very different colors and luminance. We compare the results obtained by our approach with others to demonstrate advantages in color correction quality and performance. The results in this section were obtained on a Nokia N95 8GB with an ARM 11 332 MHz processor and 128 MB RAM, using source images of 1024×768. We have also applied the approach to larger source images.

There are no comparisons to a "ground truth" of a single image that has a large field of view, as such a comparison would not be meaningful. First, our aim (and that of the relevant previous work) is to modify the colors so that human observers don't see visible artifacts. Our goal is not to provide a physically meaningful and consistent measurement from partial measurements. Just taking a difference image and calculating statistics such as LSQ error or PSNR would be fairly meaningless. Second, since the different parts of a panoramic scene may have widely differing light intensity, it may be an advantage if different areas are exposed differently, which is not possible if we take a single image with large field of view.

3.1 Comparison of Gamma Correction without and with Mean Color Matching

We compare the gamma correction using gamma-corrected color matching described in Section 2.3 with the gamma correction using gamma-corrected mean color matching described in Section 2.4 in the $sRGB$ color space.

Figure 8 shows one of the tests. In this case, there are six source images with very different colors and luminance shown in Figure 8 (bottom). Figures 8 (top) and (middle) show the results created by image stitching using gamma-corrected color matching and gamma corrected color mean matching, respectively. From the results we can see that the qualities of the panoramic images are similar. There are no color saturation and cumulative error problems. Color transitions are smoothed. However, in terms of processing speed, the previous takes about 220 seconds and the latter takes about 7 seconds which is 31 times faster. The main reason for the slow processing speed in the former approach is that a time-consuming iterative procedure such as the conjugate gradient method is needed to solve the minimization problem to obtain gamma-correction coefficients. However, the latter one can be solved in a closed form. In terms of memory consumption, the iterative procedure needs more memory then the closed-form solution. As the resolution of source images increases, the size of overlapping areas also increases, and both approaches need more time to compute color means in the overlapping areas. However, the dimensions of variables in minimization will not change. As the number of source images increases, there will be more overlapping areas, and the number of variables, which is the same as the number of source images, will increase.

More tests have been made and results are similar as above. The conclusion is that we use gamma-corrected color mean matching instead of gamma-corrected color matching in our gamma correction approach.

3.2 Comparison of Gamma Correction in Different Color Spaces

We perform the gamma correction in different color spaces and compare the performance. Figure 9 shows one of the tests. In this case, there are eight source images with very different colors and luminance in the image sequence. Figures 9 (top) and (middle) show the results created by image stitching with gamma correction using gamma-corrected color means in the $sRGB$ color space described in Section 2.4 and the $YCbCr$ color space described in Section 2.5, respectively. In this case, the results do not show large differences. The latter is a little bit better than the previous in color smoothing. We have been tested this case with more image sequences and reached a conclusion that the results obtained in the $YCbCr$ color space are in general slightly better than those obtained in the $sRGB$ color space. Notice that we perform gamma correction for the luminance component and linear correction for the chrominance components in the latter method.

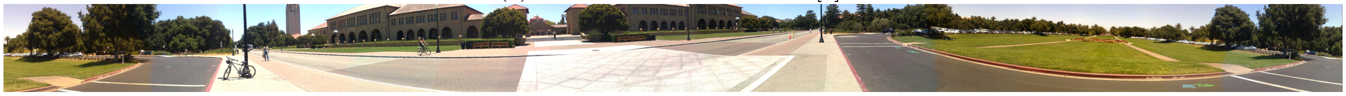
3.3 Comparison to Previous Approaches

Figure 10 shows a comparison of panoramic images created by different color and luminance correction approaches. In this application, there are 19 source images in the image sequence shown in Figure 10 (f). From the image sequence we can see that the colors and luminance of the source im-

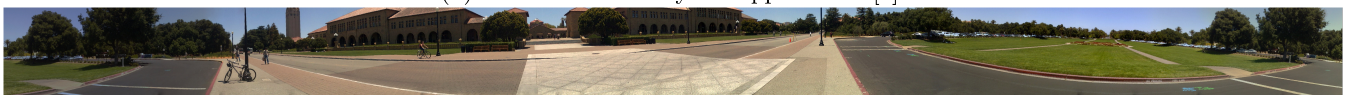
Figure 8: Comparison of gamma correction without and with using mean color matching.

Figure 9: Comparison of gamma correction in different color spaces.

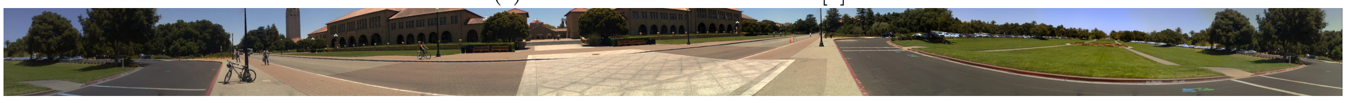
(a) Local linear correction in [7].



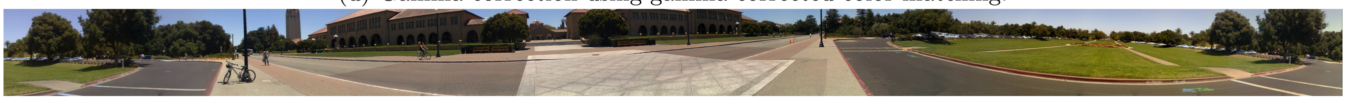
(b) Color correction by the approach in [3].



(c) Global linear correction in [1].



(d) Gamma correction using gamma-corrected color matching.



(e) Gamma correction using gamma-corrected mean color matching.

(f) Source images.

Figure 10: Comparison of results created by different color correction approaches.

ages are very different. When the source images are stitched together without any color and luminance processing, the differences of colors and luminance in the composite image can still be visible. Color correction and transition smoothing are needed to reduce these differences.

Figure 10 (a) shows a panoramic image created by image stitching with the local linear color correction described in [7]. From the result we can see the problem of pixel overflow in several areas such as the sky near the tower, the road near the bike, and so on. The whole image is too bright after color correction and many details have disappeared. Color transitions are not good, especially at the left hand side and the right hand side of the image.

Figure 10 (b) shows a panoramic image created by image stitching with the color correction described in [3] which uses linear models in the $YCbCr$ color space. There are similar problems as the result shown in Figure 10 (a). Pixels in many areas are saturated, most details are lost, color transitions in the whole image are not good, and the order of the source images in color and luminance correction process effect the final result.

Figure 10 (c) shows a result created by image stitching with the global linear color correction described in [1] in which the approach is used for luminance correction only. Here we use it for color correction in the $sRGB$ color space. From the result we can see that there are no pixel overflow problems after color correction. However, the quality of the panoramic image is still not good. Some source images are corrected too much so that the images become too dark, such as on the far left and right sides of the image. The reason is that the source images at the beginning and the end of the image sequence are too bright. For the balance of colors and luminance of the whole panoramic image, the approach performs a too severe correction for these source images.

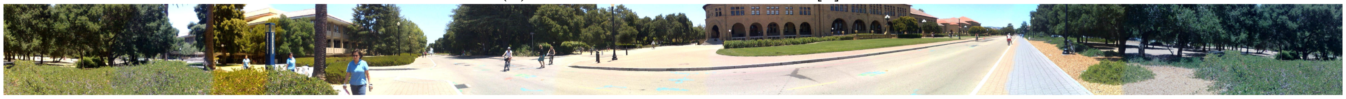
Figure 10 (d) shows a panoramic image constructed by with the gamma-corrected color matching in RGB space described in Section 2.3. From the result we can see that there are no pixel overflow problems and all details remain visible. Similar to the result of the global linear color correction, the bright source images are corrected too much on the far left and right ends of the panoramic image. As we described above, the computational cost is high, leading to slow processing speed.

Figure 10 (e) shows a panoramic image created by image stitching using gamma-corrected color mean matching described in Section 2.5. We perform gamma correction for the luminance component and linear correction for chrominance components in the $YCbCr$ color space. From the panoramic image we can see that it is the best result among these cases. All the problems mentioned above are solved. There is no pixel overflow, the corrections are not too severe. The color balance and color transitions are very good in the whole panoramic image. All details of the source images are retained in the result. There are no too dark and bright areas caused by color correction.

Figure 11 shows a second example scene. In this application, there are 16 source images in the image sequence captured in an outdoor scene. From the image sequence we can see that the colors and luminance between source images are very different, especially between the third and fourth images (image 3 is overexposed) and the third and second last images.

Figures 11 (a) and (b) show the results created by image stitching with the local linear color correction approach and the approach in [3] respectively. The quality of the compos-

(a) Local linear correction in [7].



(b) Color correction by the approach in [3].

(c) Global linear correction in [1].

(d) Gamma correction using gamma-corrected color matching.

(e) Gamma correction using gamma-corrected mean color matching.

(f) Source images.

Figure 11: Second comparison.

ite image is not good. A large part of pixels in the panoramic image are saturated and the colors of the panoramic image change a lot.

Similar to the previous application, the beginning and the ending parts of the panoramic images are too dark in the results created by the global linear correction and the gamma correction using gamma-corrected color matching, while other parts are fine. The results are shown in Figures 11 (c) and (d) respectively.

The best panoramic image among these results is the one created by the combination of gamma correction for the luminance component and linear correction for the chrominance components in the $YCbCr$ color space as shown in Figure 11 (e). From the the result we can see that color differences are reduces and color transitions are smoothed. There is no any pixel overflow problem.

3.4 More Application Results

Figure 12 shows more results obtained by applying the proposed approach which uses the combination of gamma correction for the luminance component and linear correction for the chrominance components of the source images in the $YCbCr$ color space. It can also be used in the YUV color space.

All these cases are very long image sequences with source images in very different colors and luminance. They are very hard cases in panoramic image construction.

In the case shown in Figure 12 (a), there are 19 source images with very different colors and luminance, especially around the third, eighth, thirteenth, and sixteenth images. Only a few images have normal colors. Figure 12 (a) (top) shows the result, from which we can see that these differences have disappeared. A high-resolution and high-quality panoramic image has been obtained after image stitching with the color correction processing.

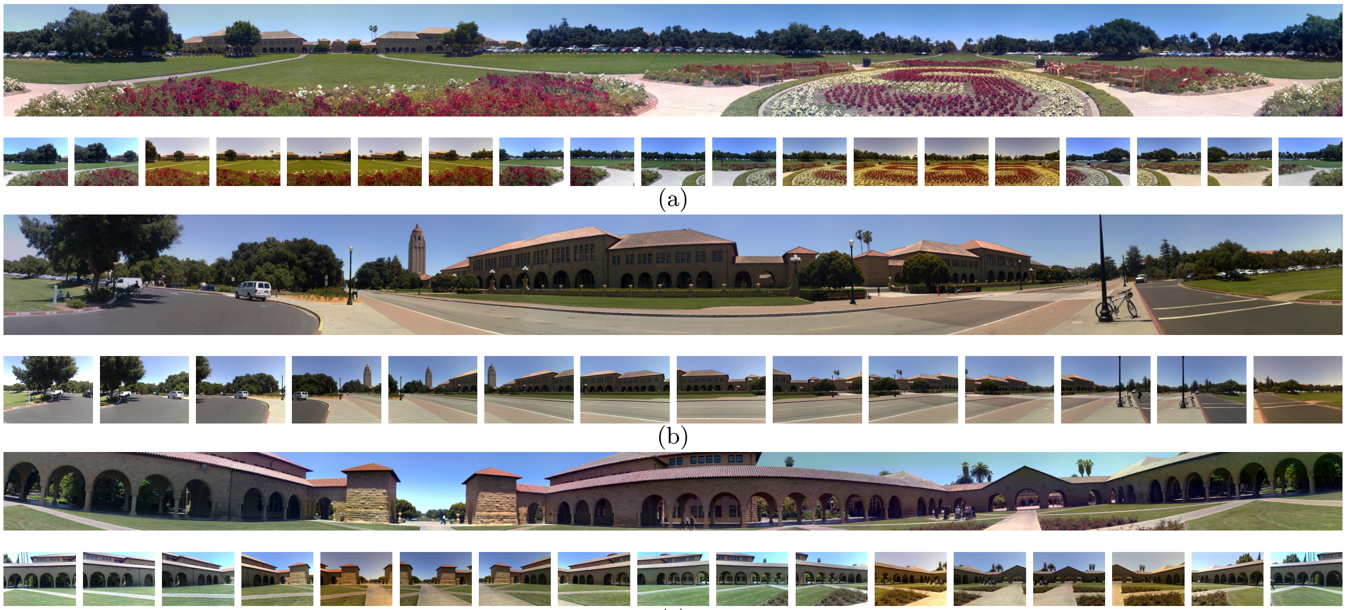
Similarly, Figures 12 (b) and (c) show other two hard cases with source images in very different colors and luminance. Again after color correction, high-resolution and high-quality panoramic images have been obtained in image stitching.

4. DISCUSSION AND CONCLUSIONS

The main motivation of this work is to develop a color and luminance compensation approach for creating high-resolution and high-quality panoramic images from long image sequences on mobile phones. A key goal is to retain the simplicity and fast processing speed of the previous approaches that use linear correction or uniform gamma correction, but avoid pixel color overflow problems during color and luminance correction and provide good color transitions for the whole image sequence.

We have presented a simple and efficient color matching approach. It matches gamma-corrected colors in the overlapping areas between adjacent source images. An objective function is created with squared differences of colors and luminance of source images in overlapping areas. The correction coefficients can be obtained by minimizing the objective function. For simplifying computation and making the approach robust to the spatial alignment errors, gamma-corrected mean color matching is used to solve the gamma-correction coefficients. In this way, the approach obtains good performance and is much faster than methods that require a non-linear solver. In the case of 6 source images, the simplified approach is 31 times faster than the one requiring a non-linear solver.

We also proposed to used the combination of gamma cor-



(a)

(b)

(c)

Figure 12: More results obtained by the proposed color correction approach.

rection for the luminance component and linear correction for the chrominance components of a source images in the $YCbCr$ or YUV color space. In this way, we can avoid pixel saturation problems efficiently and obtain good color transitions between source images.

We compared a couple of scenes processed both with our method and of previous methods. The images should be viewed and compared on computer display from the pdf as the differences are in some cases subtle. We did not perform a user study, but an interested reader can create personal opinions and the quality using additional comparison images at `http://research.nokia.com/page/9436`.

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