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COLOR CORRECTION APPROACHES IN IMAGE MOSAICKING

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Abstract—Image mosaicking is a technique of tiling digital images. Color correction is done as the initial step for mosaicking. In this paper we evaluate the effectiveness of color correction. After the finding solution for color correction, color segmentation is done which uses mean-shift and region fusion algorithm in which, it segments the images into different regions. For each of the regions, joint image histogram is computed. Then color palette mapping functions are estimated. To obtain best result with good color uniformity, regions should be segmented into small number of regions with less size. As the size of regions decreases, the uniformity of color pixels in region should contribute for a better estimation of color palette mapping function.

Index Terms— Color correction, Image mosaicking, Color palette mapping functions.

I. Introduction

Image mosaicking is a process of tilling several overlapping images. Image mosaicking finds similar application in panoramic imaging [14].But in panoramic stitching the color spaces are done very poor. In image mosaicking, registrations are done between the images [17]. There are two registrations done photometrical and geometrical registrations .For geometrical registration the images should be from same scene taken at different times, from different view points from different sensors. In case of photometrical registration, the alignment of image capturing devices is considered. Even in a set of two images taken from same camera, color representing an object may differ from picture to picture. This is known as color correction problem.

Color correction has major role for mosaicking. Color correction is often used before the tilling process to balance colors in the whole image sequence [1]. The adjustment of color palette of an image using the information from color palette of another image is also referred to as color correction problem. The registrations between the images help to build a mosaic which starts with the source image. During processing, the portions of target image and source image get overlapped which leads to computation of one or more color palette mapping functions. Several approaches are used for color correction. The first method proposed was use of single Gaussians to model the color distribution of target and source images. Another method proposed was 3D Gaussian Mixture Model [16] which has usage of multichannel modeling.

First, the color segmentation is done to overlapped region of target image which undergoes mean-shift based color segmentation process [7]. Image segmentation is the process of separating the images into different parts. In order to identify and analyze the image, it needs to extract and separate the parts of the image so that it will be possible to further use for the target image. Segmentation can be defined as a process which is based on several features such as to create histograms. In Region-fusion algorithm it segments the images into different regions with a set of parameters [2]. Histograms are created for the each input image. Creating histograms for each segmented image will show that they correspond to a region in the image. They are local joint image histogram [10], [11]. The current paper proposes the use of single joint image histogram.

Although there are several methods proposed to deal with image mosaicking. The current paper proposes a new methodology which performs the expansion of color palette mapping to the non-overlapping regions. As it is on non-overlapping region, the number of regions and size of regions become the major factors.

II. LITERATURE SURVEY

A different number of color correction approaches have been used for past several years. Commonly used color corrections are of parametric and non-parametric [1]. There are two types of parametric approaches global and local color transfer. Global color transfer provides rough mapping between images. Local color transfer is based on probabilistic image segmentation. For color distribution of source and target image single Gaussians are used [4]. As single Gaussians were inaccurate to model for complete image Gaussian Mixture Model (GMM) was proposed [5]. Then 3D GMM was proposed which fitted the data using Expectation Maximization (EM) methodology which was used to solve the problem of the performance of color correction methodologies, because each image should modeled and corrected independently. The proposed approach used in 3D GMM is evaluated using both a recently published metric and two large data sets composed of seventy images. For image segmentation EM was suggested for image clusters which uses mean-shift and region fusion algorithm. Along with this, non-parametric methods of color transfer were also used for image histograms [12], [13]. Color Correction methods are also classified into global and local [3], [6], [8]. These methods are also proposed in this paper. The following section will provide the details of proposed system.

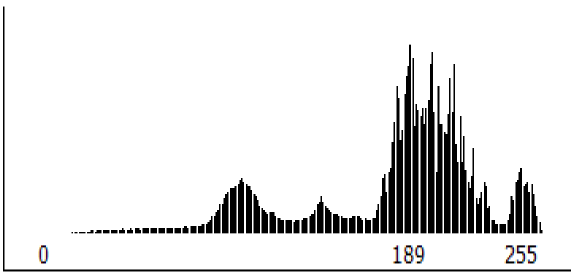
III. PROPOSED METHOD

In this paper several approaches are proposed for estimation of color palette mapping functions. First, two images are given as input. Each image is filtered using Gaussian filtering technique. Then, the images are segmented into regions using mean-shift and region fusion [7]. Then each of the regions is mapped by forming local joint image histogram. Last, the color palette mapping functions are estimated using Gaussian distribution.

A. Mean-shift and Region-fusion Algorithm

Two images are taken which are source and target image. Before doing segmentation the images are filtered using Gaussian filters. They are used to blur the images by removing noise as shown in figure 1 (c). The algorithm starts with color segmentation at overlapped image. It is done by applying mean-shift on overlapping region [7]. Mean-shift is better than EM because in mean-shift the source and target image together it segments so it will take only less time. But in EM it segments separately which takes longer time than Mean-shift. After segmenting, disconnected sets are obtained. By applying region-fusion algorithm it makes as a set of connected region and applies to input set.

Figure 1: (a) Input image



(b) Histogram of Input Image

(c) Image filtered using Gaussian filter

B. Modeling the Local Joint Image Histogram

To tackle the problem of color correction joint histogram is done [10]. For each segmented region, a joint histogram should be formed. A set of local pixels are used for constructing a histogram. The number of pixels is described by several feature points. For example, a joint histogram will have color information with n gradient values. The joint histogram will contain (n color · n gradient) entries. As each entry corresponds to particular intensity, the value stored will be the number of pixels in the image with that color and gradient of the image. And they form a single joint histogram (figure 2 (a) [2]).

To express the color palette mapping function following equation is used [2]:

$$\hat{Y} = \hat{f}i(X), \qquad (1)$$

Where $\hat{f}i$ is the estimated color mapping function for region i ,and $\hat{Y}$ is the color of the color corrected image. Consider an example of observation of joint image histograms shown in figure 2. It shows several noises due to lack of accuracy in registration of images due to factors such as vigneting [11]. The joint image histogram follows Gaussian distribution (figure 2 (b)) [14], [15]. Since the histograms are of 2D signals, the color palette mapping functions are fitted by truncated Gaussian distribution.

Truncated Gaussian distribution is better than standard Gaussian. When a noise is added to both Gaussians saturating values are shown to Truncated Gaussian. But due to several aforementioned reasons, univariate truncated Gaussian models are used. As our goal is to model color distribution in images, image sensor saturation phenomena should occur. The univariate Gaussian distribution expression is as shown [2]:

$$\hat{P}^i (X = x \mid Y = y) = \Phi(x + \Delta, \mu^i_y y\, \sigma^i_y) - (x - \Delta, \mu^i_y y\, \sigma^i_y), \qquad (2)$$

C. Estimation of Color Palette Mapping Function

After computing local color palette mapping function next step is to expand them. The estimation of color palette mapping function is done to each region if only overlapping portions are considered for color correction. Even though, color palette mapping functions are computed (figure 2 (c)) based on overlap between source and target image, it must be applied to whole image. To apply for entire image it is very complex because for all pixels it may not have corresponding color segmented region, so a second color segmentation and region fusion is run using entire image as input. Consider S as source image and T as target image. Let T^j be j^{th} color segmented region in target image. The result of the segmentation will be same as described in section 3 A. So the solution obtained for each pixel of T it will match the corresponding region in $T^{j.}$ Then the color pixel is corrected with color palette mapping function. The result obtained is complete corrected image.

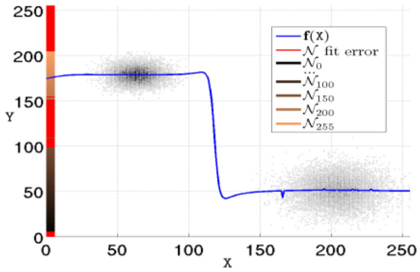
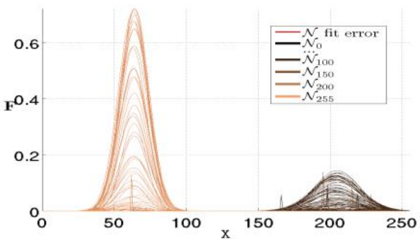
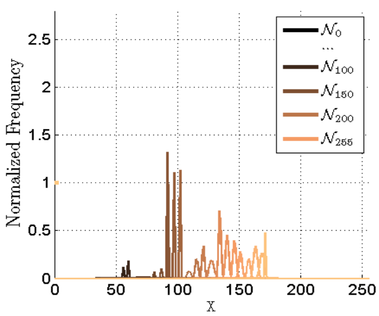


Figure 2: (a) Joint Image Histogram



(b) Modeled Gaussian



(c) Computed color palette mapping function

IV. RESULTS AND ANALYSIS

The results are presented by comparing the proposed approach with different alternatives such as modeling the color space and number of segmented regions. Color modeling is done for correcting the three color channels. In this paper standard color space RGB is used. But by comparing with *lαβ* color space [4] both are having similar results. But RGB is commonly used which gives accurate results. The algorithm starts with a source and target image. They undergo color correction. Three color channels are processed separately. Then histogram is drawn. Then the images are filtered. When it comes to color segmentation, the image is segment into different region. The joint histogram is computed for selected regions only. For example in figure 1, the selected regions are the blue sky behind the building, the white building, the green floor. For each region histogram is drawn.

Next step is to obtain color palette mapping function for each region. To see how the performance of color correction get affected we perform comparative analysis between proposed approaches which uses RGB color space and which uses *lαβ* color space.

For analysis, to test the images two different image comparison metrics were used, peak signal-to-noise ratio (PSNR) [1] and structural similarity index (SSIM) [1]. Both are similarity measures, that is, higher the value of these scores more similar is two images. The table I shows results obtained by using different parameter sets for synthesized and real image datasets. A comparative analysis is performed between the proposed approach #1, which uses RGB color space and the alternative approach #2, which corrects on *lαβ* color space. Earlier studies show that the average scores of both approaches are similar. But here from the table it can see that approach which used *lαβ* color space has more scores from which if we compare it with other algorithms it will give best results.

TABLE I

MEAN AND STANDARD DEVIATIONS OF THE **PSNR**, AND **SSIM SCORES** FOR COMAPRISON AMONG RGB AND *lαβ* COLORSPACE

	Synthesized				Real			
	PSNR		SSIM		PSNR		SSIM	
	μ	σ	μ	σ	μ	σ	μ	σ
#1	29.9	9.6	0.88	0.16	24.7	3.7	0.71	0.14
#2	28.7	8.4	0.82	0.15	23.8	3.5	0.80	0.15

In segmented regions, the number of regions is considered for obtaining good accurate results. Table II shows the comparison of the proposed approach and alternative approach based on number of regions segmented.

TABLE II

MEAN AND STANDARD DEVIATIONS OF THE **PSNR**, AND **SSIM SCORES** FOR COMAPRISON DONE FOR NUMBER OF SEGMENTED REGIONS

	Synthesized				Real			
	PSNR		SSIM		PSNR		SSIM	
	μ	σ	μ	σ	μ	σ	μ	σ
#1	18.1	9.2	0.71	0.23	24.3	3.4	0.82	0.18
#2	19.7	8.6	0.81	0.19	24.7	4.8	0.84	0.14

In table, #1 shows the method in which it uses less number of regions and #2 with more number of regions. With more number of regions, it produces only a small improvement on color effectiveness. To obtain better estimation, the size of region should be less. But when there is single region, no pre-processing color segmentation is performed.

V. CONCLUSION

This paper proposes color correction algorithms. On analysis and comparison, several observations have been concluded. The metrics PSNR and SSIM shows best average score for color space and number of regions. After the images are segmented and extended using color palette mapping functions, it is able to produce a mosaic image with no noise transitions. The proposed approaches shows that it also achieves very good result in pre-processing steps and in segmenting the regions with no color transitions.

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