AN IMPROVED BAYESIAN ALGORITHM FOR COLOR IMAGE DESATURATION

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ABSTRACT

Current digital imaging systems are unable to capture the entire dynamic range of the visible luminance, causing saturation in the very bright parts of a scene. Color distortion occurs when the amounts of saturation are different in the red (R), green (G), and blue (B) color channels. A Bayesian algorithm was developed in the past to correct the saturated pixels in raw images. For each image, it estimates the distributions of the R, G, and B color channels based on the unsaturated pixels, and then corrects the saturated pixels based on this prior distribution. In this paper, we improve this Bayesian algorithm by incorporating spatial information in the correction process. We utilize the strong spatial correlation of images as well as the correlation between the R, G, and B channels of each individual pixel to estimate the prior distributions of the R, G, and B color channels. The prior distribution of each saturated region is modeled individually based on its surrounding region, which is determined by morphological dilation. Experimental results show that our modified algorithm greatly outperforms the original Bayesian algorithm for fixing saturated pixels in color images.

***Index Terms*—**Desaturation, clipping, color restoration, high dynamic range (HDR), correlation.

1. INTRODUCTION

Conventional digital imaging devices are able to capture, store, and display a limited dynamic range of luminance [1]. If the brightness of the scene is beyond the range of the capturing device used, one or more of the red (R), green (G), and blue (B) color channels of the bright pixels will be saturated. The saturated color channels are clipped to the maximum value that the device is able to represent, and the pixel luminance is hence reduced. Different amounts of clipping usually occur to the R, G, and B values of each pixel, resulting in color distortion. Fig. 1 illustrates the color distortion artifacts due to saturation. Parts (a) and (b) are the original and oversaturated pepper images, respectively. Compared with part (a), part (b) shows color distortion caused by clipping in certain areas of the image.

This color distortion problem is frequently encountered, and needs to be carefully handled to estimate the true color of the saturated pixels. Zhang and Brainard [2] have proposed a Bayesian algorithm that estimates what the saturated channel's value would have been in the absence of saturation. The algorithm uses the unsaturated responses from the other color channels, together with a multivariate normal prior that captures the correlation in response across color channels. The algorithm has low computational cost, and is effective when the statistical properties of the saturated regions are consistent with that of the unsaturated region in the image.

Another color desaturation algorithm was recently developed by Xu, Doutre, and Nasiopoulos [3]. This algorithm utilizes the strong spatial correlation in chroma between the saturated pixels and their surrounding unsaturated pixels. The algorithm is very effective, yet computationally expensive.

In this paper, we propose an improved Bayesian algorithm for color image desaturation which is based on [2], but as performance evaluations have shown, it outperforms that method in picture quality while involving similar computational cost.

The remainder of the paper is structured as follows. Section 2 introduces Zhang's algorithm and analyses the image properties that can be used in developing a more effective color-image desaturation method. Our proposed improved Bayesian method is described in Section 3. Section 4 presents the performance evaluation of our method and Zhang's algorithm. Conclusions are drawn in Section 5.

(a) (b)

Fig. 1. Illustration of color-distortion artifacts due to saturation. (a) The original pepper image, and (b) the image saturated to a maximum value of 204.

2. OVERVIEW OF PREVIOUS BAYESIAN DESATURATION ALGORITHM

Zhang's algorithm is the state of the art desaturation algorithm that has low computational cost [2]. It uses Bayesian framework for estimating the true values of the saturated pixels. The joint distribution of the RGB color channels was used as the prior information. A multivariate normal distribution model is used to model the relation among the R, G, and B channels as follows:

$$\begin{pmatrix} X_s \\ X_k + e_k \end{pmatrix} = \begin{pmatrix} X_s \\ Y_k \end{pmatrix} \sim N\left(\begin{pmatrix} \mu_s \\ \mu_k \end{pmatrix}, \begin{bmatrix} V_s & V_{sk} \\ V_{ks} & V_k + V_{e_k} \end{bmatrix} \right), \quad (1)$$

where X_s is an $n_s \times 1$ vector of the true values of the saturated color channel(s), X_k, Y_k, and e_k are $n_k \times 1$ vectors of the true values, measured values, and measurement errors of the unsaturated color channel(s), and $n_s + n_k = 3$. The mean values of X_s and X_k are represented by μ_s and μ_k, respectively. The variances of X_s, X_k, and e_k are V_s, V_k, and V_{e_k}, respectively. The V_{sk} denotes the covariance between X_s and Y_k, and we have $V_{sk} = V_{ks}{}^T$.

Given the measured pixel values $Y_k = k$ of the unsaturated color channel(s), the conditional distribution $P(X_s \mid Y_k = k)$ of the saturated channel(s) is normal with a mean μ_{x_s} and a variance V_{x_s} [4], shown in (2) and (3):

$$\mu_{x_s} = \mu_s + V_{sk}(V_k + V_{e_k})^{-1}(k - \mu_k), \quad (2)$$

$$V_{x_s} = V_s - V_{sk}(V_k + V_{e_k})^{-1} V_{sk}{}^T. \quad (3)$$

Then, the saturated channel(s) X_s is estimated by computing the expected value of the posterior distribution, as follows:

$$E[X_s \mid Y_k = k, Y_s \geq s], \quad (4)$$

which can be calculated given (2) and (3).

The conditional variance V_{x_s} of the saturated color channel(s) X_s is smaller than the unconditional variance V_s. This variance reduction and hence more accurate value estimation is due to the additional available information provided by the strong channel correlation V_{sk}.

Based on (3), a large covariance V_{sk} results in a small V_{x_s}, which means small estimation uncertainty. The correlation between color channels is the key in Zhang's algorithm to estimate the saturated color channel(s) based on the unsaturated color channel(s). The correlation between color channels, however, varies within an image, especially between regions of different chroma. Zhang's algorithm, on the other hand, uses the same statistical model to correct all saturated areas in an entire image. Adapting the model to reflect local correlation may improve the desaturation performance.

In this paper, we proposed utilizing the strong spatial correlation in the desaturation algorithm to further reduce the conditional variance V_{x_s} of the saturated color channel(s) and hence improve the estimation accuracy.

3. PROPOSED IMPROVED ALGORITHM

Zhang's algorithm uses all unsaturated pixels in an image to estimate the prior distribution. The inter-channel correlation is used, but not the spatial intra-channel correlation. In order to utilize the strong spatial correlation of images as well as the inter-channel correlation, we propose a modified desaturation algorithm, which uses local statistics for correcting each disconnected saturated region.

In the proposed algorithm, we first identify the clipped pixels and color channels using a simple threshold. A binary image A is generated to indicate the saturated and unsaturated pixels in an image:

$$A(z) = \begin{cases} 1, & \text{when the pixel at } z \text{ is saturated} \\ 0, & \text{when the pixel at } z \text{ is unsaturated} \end{cases}. \quad (5)$$

Next, we find the set of pixels that are close to the saturated pixels for computing prior distribution model. By eliminating the pixels far from all saturated regions, the statistics of the selected pixel set should better resemble that of the saturated regions than using all unsaturated pixels in the image.

Since the saturated regions often have various sizes and irregular shapes, dilation is a good choice to find pixels in the neighborhood, regardless the sizes or shapes of the saturated regions. Dilation is defined in terms of set operations. The dilation [5] of A by B, denoted $A \oplus B$, is defined as:

$$C = A \oplus B = \{z \mid (\hat{B})_z \text{ I } A \neq \phi\}, \quad (6)$$

where A is the binary image defined in (6), B is the structuring element that determines the scale and orientation that the dilation operation "grows" or "thickens" objects (i.e., saturated regions) in A. $(\hat{B})_z$ is the reflected and translated B, and ϕ is the empty set. As a result, C includes all saturated pixels and their surrounding unsaturated pixels.

In order to take advantage of the strong local spatial correlation, pixels for estimating prior distribution model need to be localized to reflect the statistics of the different saturated regions in different areas of an image. A simple separation of disconnected objects in C groups all saturated pixels and their surrounding pixels into several local regions, i.e., C_i, where i = 1, 2, 3, …. Each region is likely to have similar statistics. An example of dilation process is given in Fig. 2. The baby image is shown in part (a). Part (b) shows the saturated regions in color superimposed on the image luma. The surrounding areas of all of saturated regions are

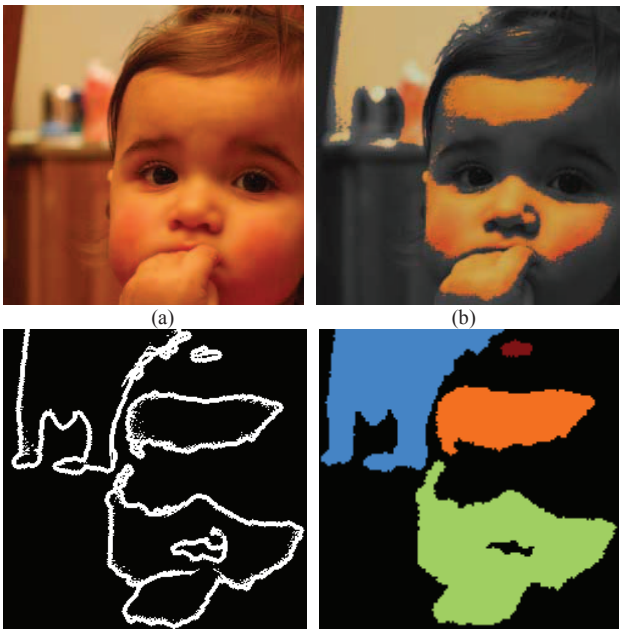

Fig. 2. Generating surrounding regions by dilation. (a) A portion of the baby image, (b) the saturated areas, (c) surrounding pixels found by dilation, and (d) separated saturated areas and their local surrounding regions; each color represents a region for which a separate set of local statistics will be calculated.

shown in white in part (c), and part (d) shows different saturated areas and their local surrounding regions by color.

Let S_i and U_i respectively denote the sets of saturated and unsaturated pixels in C_i. We calculate separate statistical parameters μ_s, μ_k, V_s, $V_k + V_{e_k}$, and V_{sk} for each region C_i, using only the unsaturated pixels U_i in its surrounding region. After the local parameters are calculated for each region, the rest of the correction is performed as in Zhang's algorithm, only with the global statistics replaced by the local ones of the surrounding unsaturated pixels U_i. That is, the saturated channel(s) in S_i is corrected using equations (2), (3), and (4), where the statistical parameters are computed using pixels in U_i. By using these local pixels when computing the prior distribution, the spatial correlation is well integrated.

We experimentally chose the optimal structuring element B in (7) to be a disk with radius four. This structuring element results in an isotropic extension of the saturated regions, with a reasonable number of pixels in the surrounding region, which offers good local statistical information for computing the prior distribution of the RGB color channels for all of our test images.

Compared with Zhang's original algorithm, the only additional steps necessary in our method are the dilation operation and splitting the dilated binary image into disconnected regions. Since these are only performed once, the extra cost is minimal. In our method, some computations are saved in calculating the statistical parameters in our method, as they only need to be computed over the surrounding region pixels, compared to being calculated over the whole image in Zhang's method. Since the surrounding regions are usually a small subset of the entire image, our method has lower complexity for that step. There is a small amount of overhead for keeping tracking separate statistics of different surrounding regions. Overall, our method has very similar complexity to Zhang's method.

4. EXPERIMENTAL RESULTS

In order to objectively test our method, we use conventional eight bits per channel color images. We introduce saturation into the images by clipping the R, G or B values that are above a threshold (e.g., 255×0.8). Then, we enhance the saturated images using Zhang's algorithm and our proposed algorithm, and compare the results to the original images without clipping.

To evaluate the algorithm performance in terms of image fidelity, we compute the PSNR (averaged over R, G, and B channels) and S-CIELAB [6] (averaged over the saturated pixels) of each test image for: 1) the saturated image, 2) the desaturated image generated by Zhang's algorithm, and 3) the desaturated image produced by our improved algorithm. The quality comparison for a set of representative images is listed in Table I. Note that S-CIELAB is a distance measure; a lower value means better quality. From the table, we observe that while both Zhang's

TABLE 1
OBJECTIVE QUALITY COMPARISON BETWEEN DIFFERENT ALGORITHMS

Image	*PSNR (in dB)*			*S-CIELAB*		
	Clipped	*Zhang's*	*Ours*	*Clipped*	*Zhang's*	*Ours*
girl	42.2	39.7	48.5	0.98	1.51	0.40
landscape	25.7	28.7	31.7	1.87	1.41	0.87
baby	32.1	29.1	38.9	1.24	1.86	0.43
mountain	30.0	34.3	40.8	1.65	0.91	0.30
shoes	25.3	32.9	32.0	2.00	1.02	0.82
sunset	21.7	20.8	25.7	3.04	3.47	2.02
kodim03	34.3	35.2	36.6	2.30	2.25	1.82
kodim05	33.6	35.7	36.5	2.25	1.83	1.77
kodim06	25.2	28.2	26.1	3.44	1.97	2.89
kodim12	28.4	33.7	31.8	2.08	0.81	0.74
kodim16	35.1	35.9	36.5	2.16	1.98	1.54
kodim21	32.4	33.6	34.2	3.03	2.51	2.22
kodim23	29.6	31.2	33.4	1.70	1.40	1.01
Average	**30.4**	**32.2**	**34.8**	**2.14**	**1.76**	**1.30**

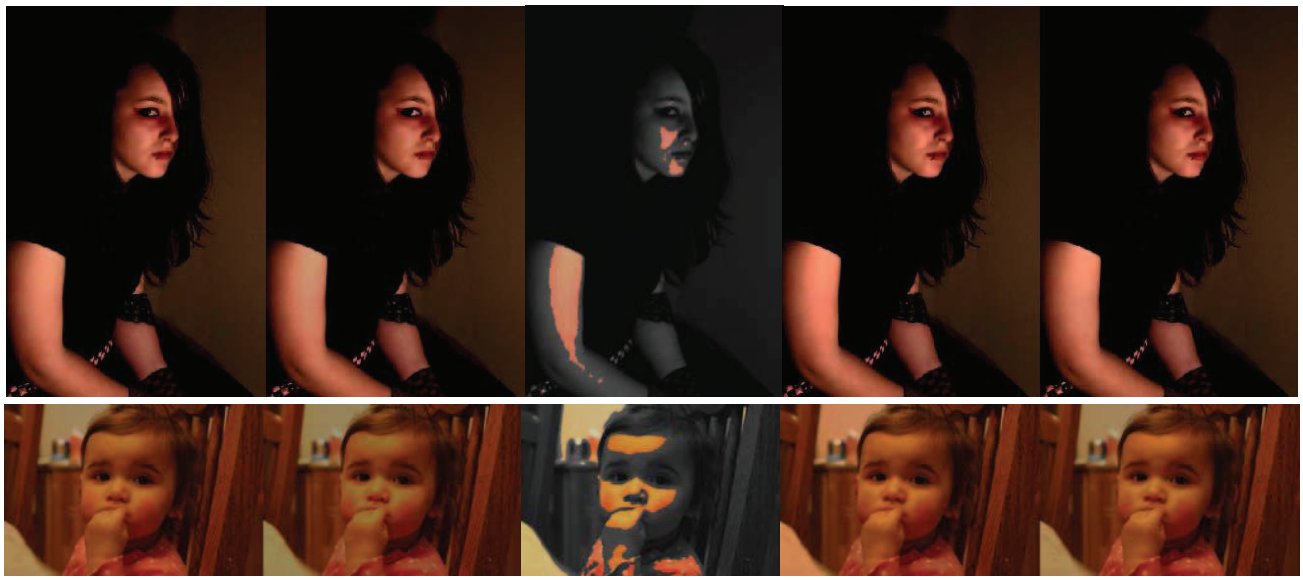

Fig. 3. Results of clipped pixel enhancement for images girl and baby. For each row, we show (from left to right) the original image, saturated image, saturated areas superimposed on the image luma, desaturated image using Zhang's algorithm, and desaturated image using our proposed algorithm.

algorithm and our proposed algorithm enhance the saturated color channels, our proposed method outperforms Zhang's algorithm by an average of 2.61 dB in PSNR and 0.46 in S-CIELAB over the test images. Our method performs well especially for images where the local statistics are inconsistent with the global statistical model.

Subjective quality of the desaturation algorithms is also evaluated and shown in Fig. 3. For each representative image, we show (from left to right) the original image, saturated image, saturated areas superimposed on the image luma, desaturated image using Zhang's algorithm, and desaturated image using our improved algorithm. From Fig. 3 we observe that the saturated images have color distortions due to clipping. While Zhang's algorithm corrects such distortion for most saturated regions, it miscorrects some areas and results in further color distortion. An over-correction example can be seen in the background area of the baby image. Such miscorrection happens when the statistical model of a saturated region differs from the global statistical model of the unsaturated pixels in the image. Compared to Zhang's algorithm, our algorithm gives better or comparable subjective quality, while avoiding the blocky artifacts, such as the arm area in the girl image. The saturated pixels in the arm area have very different statistics from the dark portion of the image. Therefore, using the global prior distribution model derived from all the unsaturated pixels in the image results in poor performance. Our algorithm uses nearby pixels to generate local statistics for the clipped pixels in the arm and leads to better results.

5. CONCLUSIONS

In this paper, we have investigated correcting saturation in color-images. We have proposed an improved Bayesian algorithm based on Zhang's algorithm. Our method utilizes the images' strong spatial correlation in addition to the correlations between R, G, and B color channels. We use a dilation operation to find a surrounding area for each clipped region in the image, and use statistics calculated based on this surrounding region for correcting the saturated pixels. Experimental results show that our proposed method effectively corrects the saturated color images, and outperforms the original Bayesian algorithm in both objective and subjective image qualities. The quality gain is by an average of 2.61 dB in PSNR and 0.46 in S-CIELAB.

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