Spatially-Adaptive Log-Chroma White Balance

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Abstract

Auto white balancing (AWB) is a fundamental problem in computational photography. In this paper, we implement a Spatially-Adaptive Log-Chroma White Balance (SALC-WB) algorithm on raw images. Traditional methods, such as Gray World and Shades-of-Gray, compute global statistical estimations that often fail in locally varied lighting. Our pipeline combines local statistical estimation in log-chroma space with a Shades-of-Gray prior.

SALC-WB, unlike existing methods that require training or complex optimizations, is a simple and efficient AWB algorithm that recovers accurate luminance and reduces local artifacts used by older methods. This approach provides a solution for high-quality white balancing.

1. Introduction

When capturing a scene with a digital camera, the sensor captures a wide range of illuminants [1]. The goal of AWB is to correct these variations in illumination so that the rendered image reflects the true colors of the scene [2]. Despite the importance of white balancing, it still remains a challenging problem to solve, especially in real time on limited hardware.

Auto White Balancing algorithms come in a broad range of statistical models, gamut-based approaches, learning-based, deep learning, and physics-based methods. Statistical models such as Gray World and White Patch estimate the scene illuminance using global assumptions [5]. Many new white balancing algorithms and color constancy papers use heavy optimization tricks and extensive training data [6]. However, there is a thought to pick and choose from these algorithms—to create an amalgamation of methodology.

To overcome the challenges of both statistical inaccuracies and deep learning's dataset reliance, we propose Spatially-Adaptive Log-Chroma White Balance (SALC-WB). This method was designed to address the shortcomings of purely global or purely learned approaches. Our pipeline functions in log-chroma color space [3] used in most modern color constancy methods. Working in log-chroma space allows us to reframe the problem of illumination estimation into a two-dimensional problem [3]. Computing local statistical estimations within this space, SALC-WB captures varying illumination without requiring iterative optimizations.

The algorithm preserves luminance through geometric-mean normalization which reduces haloing and box (window) artifacts often seen in more juvenile implementations [8]. The benefit of combining both local and global estimates is the adaptation efficiency of locally inconsistent lighting without affecting the global image balancing. The tests performed on this algorithm were raw images from a Sony IMX135 sensor [9], where SALC-WB is able to produce an accurate, artifact-free white-balanced result that outperforms traditional global estimations without the heavy compute of learned models [8].

Our paper will proceed as follows: In section 2 we will review related work in color constant and adaptive white balance algorithms. In section 3 we will describe the proposed Spatially-Adaptive Log-Chroma White Balance algorithm in further detail. In section 4 we will present our findings and evaluation results on our raw image dataset. In section 5 we will compare the strengths and limitations of this approach to existing methods. Finally, in section 6 we will outline directions for further research and conclude.

2. Related CC and AWB algorithms

In the Book *of Optics*, Alhazen (Ibn al-Haytham) observed that "the sentient perceives that the visible object is luminous and that the light seen in the object is other than the color and that these are two properties" [4]. This insight paved the way for the study of modern color constancy. Computational approaches to color constancy mirror this philosophy of separating issues of perceived illuminants and true reflectance [3].

The problems of Color Constancy (CC) and Auto White Balance (AWB) are tied quite closely together but differ in preservation and practical implementation. Color constancy concerns itself with the preservation and recovery of surface reflectance under varying illuminations. Auto white balance, however, is the implementation of color constancy within the camera processing pipeline [7]. This relationship between AWB and CC can be described as the classic mathematical definition: *all squares are rectangles, but not all rectangles are squares*. AWB is a subset of CC—all AWB problems *are* CC problems—therefore by a set definition, not all CC problems are AWB problems in terms of scope and formulation.

2.1 Color Constancy Algorithms

Early color constancy algorithms estimate scene illuminance such as Gray World and White Patch using global statistics [3]. These assumptions about the image color distribution fail to account for non-uniform lighting. Spatial color constancy approaches compute region-based analysis [6] which do account for local differences but are often very costly. Modern CC approaches formulate CC in log-chroma space, where illumination estimates become invariants of the overall intensity changes [7].

An important substudy of CC are learning-based approaches [3, 7] to further improve accuracy. These models, however, require expensive computations and are oftentimes not suited for real time applications. To build a rounded overview of approaches, many branching topics and areas of research borrow from one another [6].

2.2 Auto White Balance Algorithms

Within the camera processing pipeline, AWB is responsible for illumination correction. Often computed using Gray world or Shades-of-Gray assumptions, these approaches struggle with strong color bias, varied lighting conditions, and spatially localized-illuminants which leads to artifacting [5].

Spatially adaptive AWB techniques like ours address most of these issues using region-based methods that negate many biasing issues. But to take it a step further, borrowing from CC research such as color space transforms, smoothing priors, and statistical blending [6] between local and global estimations negates the haloing effect many combinatorial AWB algorithms have.

3. Method

The proposed Spatially-Adaptive Log-Chroma White Balance (SALC-WB) algorithm achieves stable illumination correction by combining local statistics with a global prior. This method computes in log-chroma space.

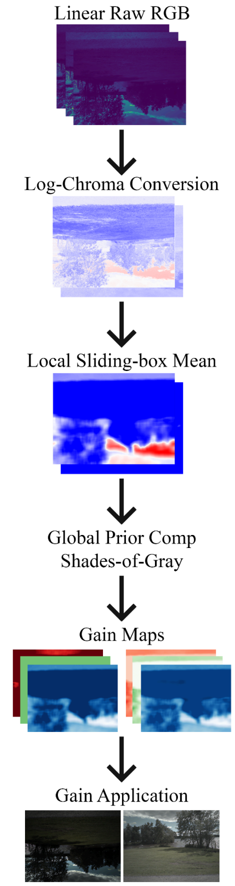


Figure 1: High level pipeline application

3.1 Local Log-Chroma Estimation

Given a linear RGB image as input $I = [R, G, B]$, the pipeline first converts to log-chroma space. We can calculate logarithmic ratios [3, (1)] to represent chromaticity with respect to the green channel:

$$I_u = log(I_g/I_r) \quad I_v = log(I_g/I_b) \tag{1}$$

This approach decouples chromaticity from intensity and converts the problem into a two-dimentional problem [3].

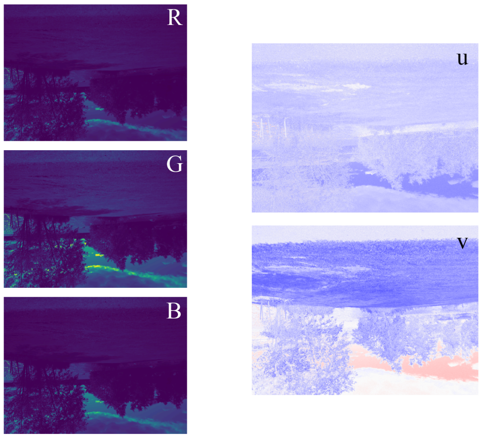


Figure 2: Composition of linear to log-chroma

A sliding-window mean is then independently applied to the u and v channels. This keeps large chromatic shifts constrained to prevent large bias and keeps the image stable.

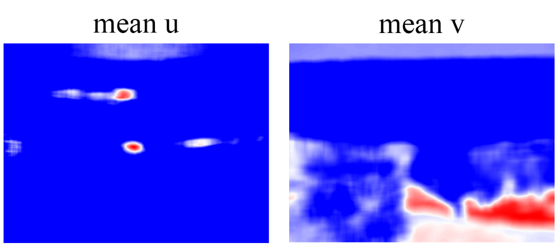


Figure 3: Sliding-window result

3.2 Global Shades-of-Gray Prior

In order to keep each of the local estimations stable, SALC-WB uses a basic Shades-of-Gray prior computed using a Minkowski p-norm [5] to produce a mean of each channel. Dividing by our global norm and prior scale gives us the final shades-of-gray prior.

$$C = R, G, B \quad \mu_C = (\frac{1}{N}\sum_{i=1}^{N} C_i^p)^{1/p} \tag{2}$$

A global normalization factor is then defined that of which we can compute per-channel gains.

$$\mu_{avg} = \frac{\mu_R + \mu_G + \mu_B}{3} \quad g_C^{prior} = \frac{\mu_{avg}}{\mu_C + \epsilon} \tag{3}$$

Where p can be defined as 4 for our needs while ϵ is some constant $1e-8$ for numeric stability [5].

3.3 Gain Computation and Luminance Preservation

Color correction gains are recovered from the estimated u, v log-chroma values.

$$g_r = exp(-\overline{u}), \quad g_g = 1, \quad g_b = exp(-\overline{v}) \tag{4}$$

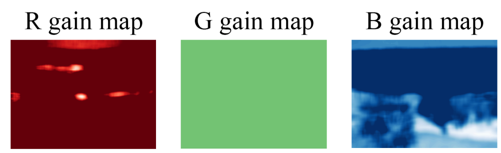


Figure 4: Channel gain maps

To preserve luminance, we then normalize the local gins so that the geometric mean equals 1.

$$\overline{G} = (g_r * g_g * g_b)^{1/3} \tag{5}$$

$$g_r = \frac{g_r}{\overline{G}}, \quad g_g = \frac{g_g}{\overline{G}}, \quad g_b = \frac{g_b}{\overline{G}} \tag{6}$$

Figure 5: Normalized channel gain maps

3.4 Spatial Smoothing and Gain Constraints

Lastly, we apply our global prior to our local sliding-window. To do so, we multiply our prior and local to some power alpha as a clipping mask

$$g_c' = (g_c^{prior})^{\alpha} * (g_c^{local})^{1-\alpha} \tag{7}$$

Figure 6: Post channel composition

Where $\alpha \in [0, 1]$ controls the contribution of the global prior. We can then smooth our gain results [6] with a simple gaussian filter.

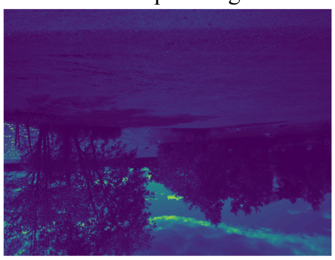
$$g_r = \frac{g_r'}{g_g' + \epsilon}, g_g = 1, g_b = \frac{g_b'}{g_g' + \epsilon}, \tag{8}$$

This reduces the block artifacts and discontinuities but is still much more simple than the inspiration for this method [6].

4. Results and Evaluation

Performance was evaluated across two datasets within the Sony IMX135 superset [9]. These tests provide a quantitative evaluation of the proposed SALC-WB algorithm on raw images.

Raw input image



Processed raw image

Final output image

Figure 7: Image pipeline results

The resulting image is color balanced. Saturation and other color balancing effects are absent making the image look dull, but that is not a part of this imaging pipeline step. Here we can compare the final output image to the reference image in the dataset.

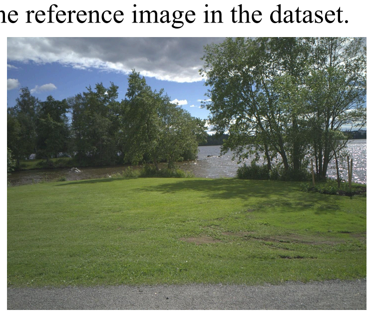


Figure 8: Reference dataset image

4.1 Metrics

White balance performance is often measured in degrees of angular error. This measures the estimated illuminant and the reference illuminant. As a standard metric in color constancy research, it produces an estimated accuracy of chromaticity.

4.2 Results

A short summary of the results ran through each of the subsets of data for the Field Camera and Lab Scenes. Each set was tested for error in outdoor, large lighting in the field camera dataset and indoor, sharp lighting with the lab scenes dataset

Sony IMX135

Metric	Field Camera	Lab Scenes
Mean	4.757°	3.390°
Std	3.085°	2.140°
Min	0.079°	0.567°
Max	14.350°	7.185°
Error	1.67° - 7.85°	1.29° - 5.49°

Table 1: Performance on the Sony IMX135 dataset [9]

On average, SALC-WB produces a lower mean angular error in the controlled lab scenes; this is expected. The difference between the lab scenes and field camera scenes however are much closer than expected and is a nice result. It shows the algorithm is able to locally adapt and also composes global stability. The log-chroma estimation reduces the color artifacts while the global shades-of-gray prior effectively reduces the over-correction.

In comparison, the worst-case angular errors reported seem reasonable when compared to various algorithms and datasets that use similar techniques. Context is paramount when understanding differing algorithms since SALC-WB does not use any training data, calibration, or optimizations. These results are favorable and display an expected trade-off between accuracy and computational simplicity.

6. Conclusion

We have presented SALC-WB, a spatially-adaptive log-chroma white balance algorithm that is lightweight and accurate. By combining local estimation in log-chroma space and global Shades-of-Gray prior, the proposed method effectively corrects colors while preserving image luminance.

Results on the raw image dataset captured with a Sony IMX135 demonstrates that SALC-WB achieves comparable results to other methods. Across both the controlled lab scenes and field camera images, the method produced the expected angular error while avoiding common artifacts and remained stable under broad lighting conditions.

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