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The GYYCy Color Filter Array

Tripurari Singh
Image Algorithmics, Bethesda, MD 20816, USA
Mritunjay Singh
Image Algorithmics, Irvine, CA 92620, USA
Arnav Singh
Image Algorithmics, Irvine, CA 92620, USA

Abstract

The automotive industry has developed several high sensitivity CFAs, such as RCCB, RCCG and RYYCy, by substituting the primary color filters in the standard Bayer color filter pattern with lighter colors. This has had the side effect of lowering color accuracy, and more importantly, color separation of important traffic features such as traffic lights and lane markers.

All high sensitivity automotive CFAs retain the red filter given the importance of red lights and signs. Counter-intuitively, this is a sub-optimal strategy, since the ideal red spectral response, being a difference of two Gaussians, has a large negative lobe that cannot be accurately approximated by a color filter.

A more accurate method of capturing red is as a difference of yellow and green, which is analogous to the difference of L and M retinal cones that the human visual system uses. Remarkably, this results in both an improvement of sensitivity and color accuracy instead of trading off one for the other.

Introduction

The automotive industry has developed several high sensitivity CFAs, such as RCCB, RCCG and RYYCy, by substituting the primary color filters in the standard Bayer color filter arrays with more transmissive filters of lighter colors. The omitted primary is then calculated during the color correction step. These imagers incur the following penalties:

1. Inaccurate spectral response leading to poor metamerism.
2. Strong color correction that amplifies noise and demosaicking artifacts.
3. Mismatched transmittance of filter colors leading to reduced dynamic range
4. Wide band color filters requiring lenses with low chromatic aberration, which are bulky and expensive for high resolution cameras. Imagers with narrow bandwidth color filters can correct chromatic aberration by aligning the different color planes. This works for narrow band color filters but not wide band color filters because each color plane is captured with high MTF in the former but not the latter.
   RYYCy cameras adopt the hybrid approach of correcting chromatic aberration over the long and medium wavelength part of the spectrum but not over the short wavelength part of the spectrum because few important traffic features are in blue.

The substitution of primary color filters with clear filters yields larger improvement in low light SNR than substitution with secondary color filters and is accompanied by correspondingly larger penalties.

Addressing the metamerism associated with high sensitivity CFAs is the primary focus of this paper. Long and medium wavelengths of the visible spectrum are especially important for automotive applications as they cover the red, yellow and green traffic lights. CFAs containing both red and green color filters such as RGGB and RCCG excel at traffic light separation while RCCB and RYYCy suffer from red-yellow traffic light confusion [1] on account of the inaccurate green calculated in the color correction step. [1] explores shifting the red response to longer wavelengths to ameliorate this traffic light confusion. In this shifted red CFA design, both red and green are less accurate than conventional RGGB/Bayer, but work together to separate red and yellow traffic lights. The visual quality, or other side effects of inaccurate red and green are not investigated.

The short wavelength part of the spectrum, while not as important as the medium and long wavelength, is essential for white-yellow lane marker separation. RCCG, with the poorest blue among all high sensitivity CFAs, has difficulty with white-yellow separation under sodium vapor illumination.

High sensitivity CFAs also have visually poor colors with RCCG being the worst offender. This problem can be greatly ameliorated by performing white balance in the sensor sharpened color space [2, 3] including the RGB color space of typical image sensors. This method of white balance requires two color space conversions, a conversion from the CFA color space to the sharpened color space followed by white balancing and another conversion to the output color space, such as sRGB. As of the writing of this paper this method is not commercially used with white balance typically being performed in the image sensor itself prior to HDR merge.

The rest of this paper is organized as follows: in the next section we describe a color filter design that achieves both greater sensitivity and greater color accuracy instead of trading them off. In the following section we explore methods for further increasing sensitivity, albeit at the expense of accuracy in the less important blue part of the spectrum. Finally, in the last section, we experimentally evaluate the performance of proposed CFAs.

Spectral response as Gaussians and difference of Gaussians

For a colorimetric camera with ideal color filters, Gaussian spectral responses suffice for green and blue [4]. The ideal red spectral response, on the other hand, is a difference of two Gaussians corresponding to the L and M cones of the human retina. As

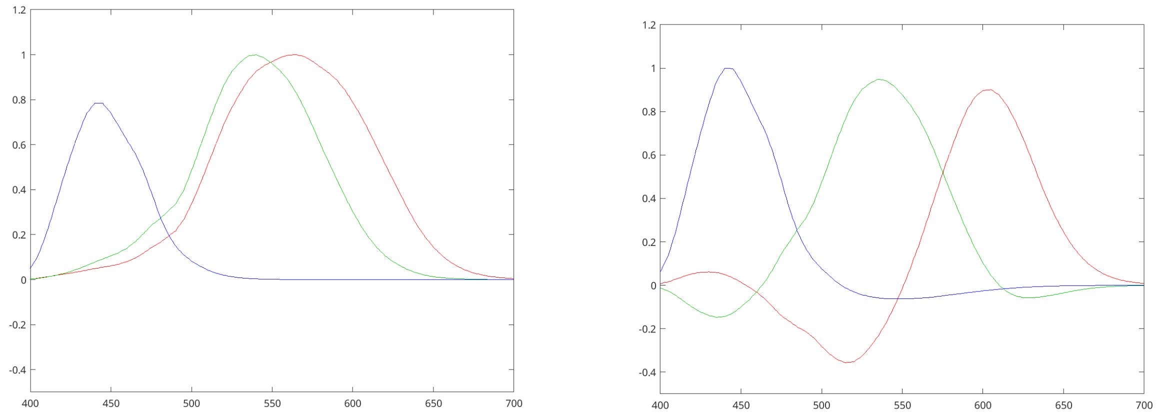


Figure 1: Spectral sensitivity of a hypothetical LMS image sensor (left), and spectral sensitivity after conversion to the sRGB color space (right), representing the response of ideal color filters.

shown in figure 1, this is a complex spectral shape with a large negative lobe that cannot be mimicked by a physical filter. Practical red filters, as a result, are poor approximations of the ideal red filter.

The obvious solution to this problem is to use Gaussian filters modeled on the L, M cones of the human retina and set red as their difference. While M can be well approximated by existing green pigments, the L color filter array material is not commercially available as of writing of this paper. Yellow pigment can be used as a rough approximation for L and the resulting YGB color space, while not colorimetric, has superior metamerism than the RGB color space of Bayer sensors, see figure 2. Since yellow is a light color, the GYYB CFA is also more sensitive than RGB. This results in an improvement of both sensitivity and color accuracy instead of trading off one for the other as is done by other high sensitivity automotive CFAs.

It should be noted that YGB requires stronger color correction which amplifies noise and demosaicking artifacts. Strong color correction, however, is not unique to GYYCy and is needed by all high sensitivity CFAs and the resulting trade offs have been accepted by the automotive industry.

Trading Blue quality for Sensitivity

While GYYB has better color accuracy and sensitivity than traditional RGGB, its sensitivity falls short of RYYCy, RCCB and RCCG. This shortfall, caused by the high density of blue pixels which have low quantum efficiency, can be addressed by either reducing the density of blue pixels or replacing blue with a lighter color filter.

4X4 YGB CFA

A 4x4 CFA with lower density of blue pixels is shown in figure 3. This design is based on the LMS CFA of [5] and uses the same demosaicker. This 4x4 YGB CFA is competitive with RYYCy in sensitivity and has better metamerism than RGB, RYYCy, RCCB and RCCG. Furthermore, the high density of green and yellow compensates for the noise and demosaicking artifact amplification in the red channel by the strong color correction.

GYYCy

The other approach to improving sensitivity of GYYB is to replace blue with cyan to obtain GYYCy. Blue is now calculated in the color correction step by subtracting green or yellow, or both, from cyan. Roughly speaking this attempts to approximate the Gaussian response curve of blue with a difference of Gaussians. This is the opposite of the approximation problem faced by conventional red filters and performs poorly for similar reasons.

Fortunately, blue is not an important primary for automotive applications, with the exception of white-yellow lane marker separation. White and yellow differ mainly in blue, but this difference is large enabling all automotive CFAs to separate the two under all illuminants except for sodium vapor lamps. Under sodium vapor illumination RCCG struggles with white-yellow separation. GYYCy performs better than RCCG and RYYCy but not as well as RGGB and RCCB. Fortunately, GYYCy's white-yellow lane marker separation is adequate.

Replacing blue with clear filters is an option, but not an attractive option, because of white-yellow separation problems similar to RCCG. Additionally, clear filters incur the chromatic aberration lens size and cost penalty described in the introduction. Replacing blue with magenta similarly incurs this chromatic aberration penalty while providing lower sensitivity improvement than cyan, making it another unattractive option.

Experiments

In this section we experimentally compare the performance of GYYB and GYYCy against the standard RGB/Bayer and also RYYCy, RCCB and RCCG. We evaluate color separation, which is the focus of this paper, and also low light SNR and dynamic range of their luminance channels. Improved low light SNR compared to RGB/Bayer without significant degradation in dynamic range and color separation constitutes good performance.

Raw Image Generation

Our simulation uses a hyperspectral image of the Macbeth Color Checker chart [6], and hyperspectral renders of traffic lights and lane markers using the spectrum given in [7]. The hyperspectral image cube consists of 300 bands, each rendered at twice

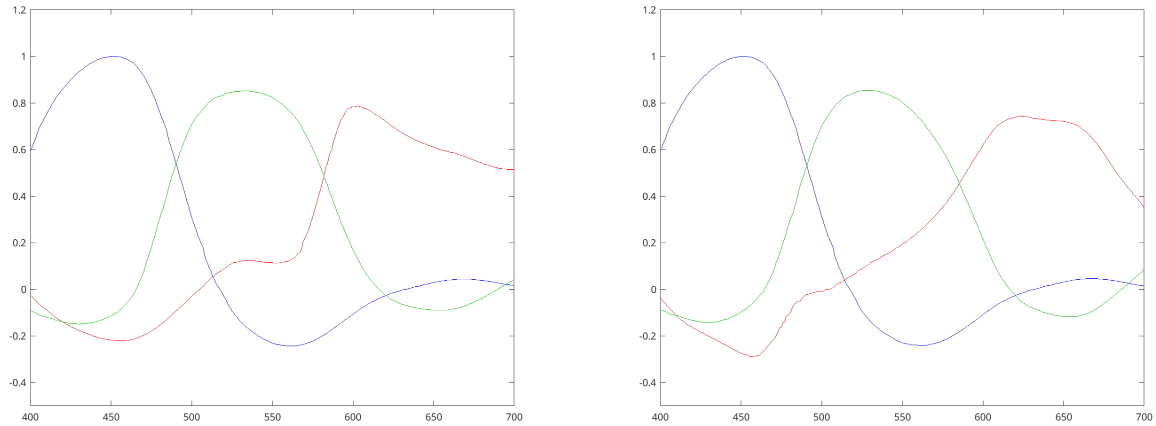
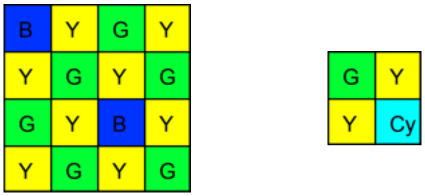


Figure 2: Spectral sensitivity, after color correction, of the Onsemi AR0820 RGB Bayer image sensor (left), and the proposed GYYB (right).



B	Y	G	Y
Y	G	Y	G
G	Y	B	Y
Y	G	Y	G

G	Y
Y	Cy

Figure 3: The 4X4 YGB CFA left, and the GYYCy CFA (right).

the target resolution and decimated after the application of a lens model in order to simulate MTF and aliasing. The lens model is diffraction limited with an Airy Disc diameter of 2 pixels which is typical of automotive cameras. The raw generation pipeline is shown in figure 4.

We simulate the LED traffic lights, which is the type of traffic light most prone to red-yellow confusion. Red-yellow confusion arises from poor metamerism of LED spectra and is worsened by the false color from aliasing. It should be noted that noise does not materially add to color confusion since traffic lights are always bright. We simulate the three popular LED traffic light lattices - the square, the quincunx and the concentric circular.

Lane markers are problematic in low light where noise exacerbates color differences diminished by metamerism. We render white and yellow lane markers as shown in figure 8 using the spectrum of [7].

We mosaic the image by integrating, over visible wavelengths, the product of the hyperspectral image with the quantum efficiency of the relevant color filters overlaid on the OnSemi AR0820 [8]. We model noise from a sensor with $1.5e^{-}$ read noise and a conversion gain of 0.19 quantization levels per electron. We simulate D65 as well as LED headlights and sodium vapor lights [7].

Image Signal Processing

The image signal processing pipeline used by our simulation is shown in figure 5. It has the following features:

1. white balance relies on a known gray patch in the image
2. demosaicking is performed by the popular “DLMMSE” algorithm [9] because of its low false color and good performance on noisy images
3. the color correction matrix that minimizes mean squared error on the hyperspectral image of the Macbeth Color Checker of [6] is used

Color Separation

Color separation, such as the ability to distinguish red and yellow traffic lights or white and yellow lane markers, depends on the average color values of the image features in question, and also on the variance of these color values. The variation of colors values, in turn, depends on noise and aliasing artifacts.

Color correction does not help color separation, since color correction that increases the difference between colors also correspondingly increases the variance associated with these colors. This can be readily seen for linear color correction and also holds for well behaved non-linear correction that can be locally approximated by linear functions.

White balance, on the other hand, affects color separation by affecting the amount of false color generated by the demosaicker. While the vision system consuming the imagery can, in principle, reverse unhelpful color correction, aliasing induced by unhelpful white balance cannot be reversed after the fact. Given the importance of correct white balance, we ensure that each of our images has a known gray patch for the purpose.

We plot the R and G values of traffic light images as a 3D histogram. We omit the B values since it does not play a role in traffic light color determination. Each of red, yellow and green traffic lights generate a histogram peak and good separation of peaks represents good separation of traffic light colors. The traffic light histograms of RGGB, GYYCy, RYYCy, RCCB and RCCG are shown in figure 7.

For white-yellow lane marker separation, we choose the IC_tC_p color space for its convenient depiction of white and off-white colors in a high dynamic range setting. We plot 3D histograms with C_t, C_p as the two color axes. The lane marker histograms of RGGB, GYYCy, RYYCy, RCCB and RCCG under sodium vapor illumination are shown in figure 9.

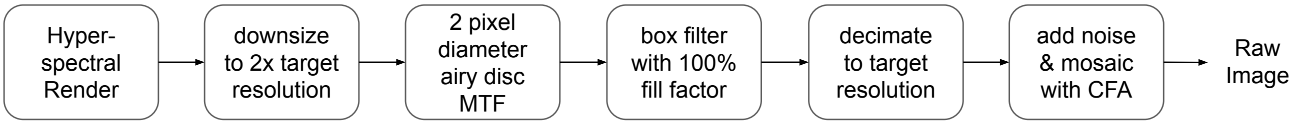


Figure 4: Raw generation pipeline starting with a high resolution hyperspectral render

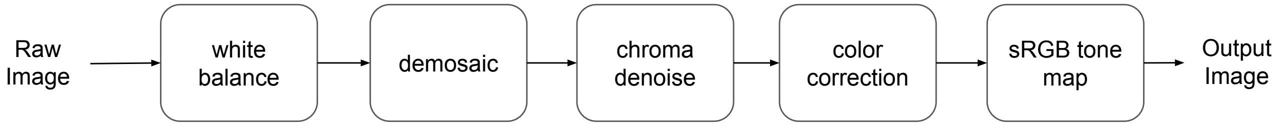


Figure 5: Image Signal Processor Pipeline

SNR and Dynamic Range

When the Bayer primaries are replaced with lighter color filters, low light SNR increases, while the light intensity at which the sensor saturates decreases. Green is the most sensitive color in the Bayer CFA and its saturation determines the upper end of the usable dynamic range. Compared to green pixels clear pixels saturate at 6.3 dB lower light intensity and yellow pixels saturate at 3.4 dB lower light intensity.

SNR improvement is a complex function of individual pixel SNR and the demosaicking algorithms. We measure low light, read noise limited SNR on the 18% gray panel of the Macbeth Color chart [6]. Our SNR and dynamic range simulation results are summarized in table 1.

CFA	Low Light SNR	Bright Light Saturation Point	Dynamic Range
Bayer	Reference	Reference	Reference
RCCB	+2.75 dB	-6.3 dB	-3.55 dB
RCCG	**+3** dB	-6.3 dB	-3.3 dB
RYYCy	+2 dB	-3.4 dB	-1.4 dB
GYYCy	+2.5 dB	-3.4 dB	**-0.9** dB

Table 1: SNR and Dynamic Range

Conclusion

This paper proposes a new CFA optimized for automotive applications that improves SNR, while maintaining good dynamic range and color separation of important traffic features. It does not require bulky lenses that provide the chromatic aberration correction necessary for clear and magenta pixels.

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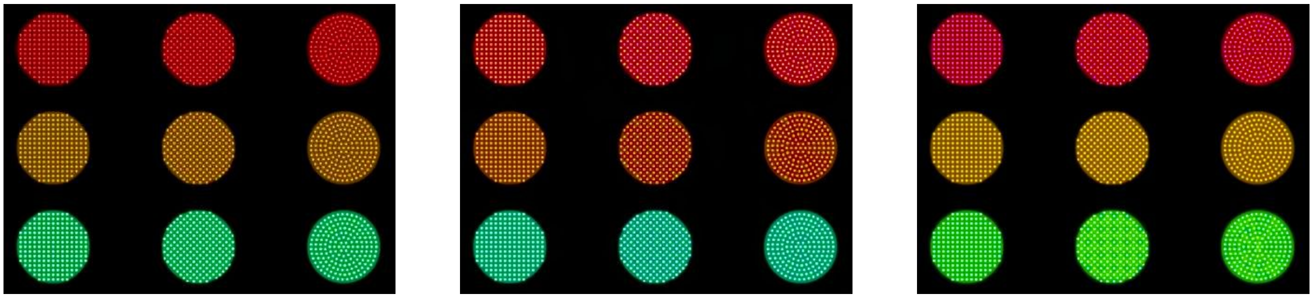
Author Biography

Tripurari Singh received his Bachelors in Computer Science from the Indian Institute of Technology, Delhi, (1993) and his PhD in Computer Science from the Johns Hopkins University (1999). Thereafter he worked in the Operations Research industry, developing stochastic optimization algorithms, before switching to image processing. His work has focused on CFA design and the processing of raw sensor data in the presence of white/clear pixels, infrared pixels, chromatic aberration, multiple rounds of pixel binning and high chrominance resolution.

Mritunjay Singh has a background in Physics from Indian Institute of Technology, Mumbai and Caltech. Thereafter he worked in the Operations Research industry, developing stochastic optimization algorithms, before switching to image processing. His work has focused on CFA design and the processing of raw sensor data in the presence of white/clear pixels, infrared pixels, chromatic aberration, multiple rounds of pixel binning and high chrominance resolution.



(a) Bayer (b) RCCB (c) RCCG

(d) RYYCy (e) GYYCy

Figure 6: LED Traffic Lights, with three popular LED patterns, after demosaicking and color correction.

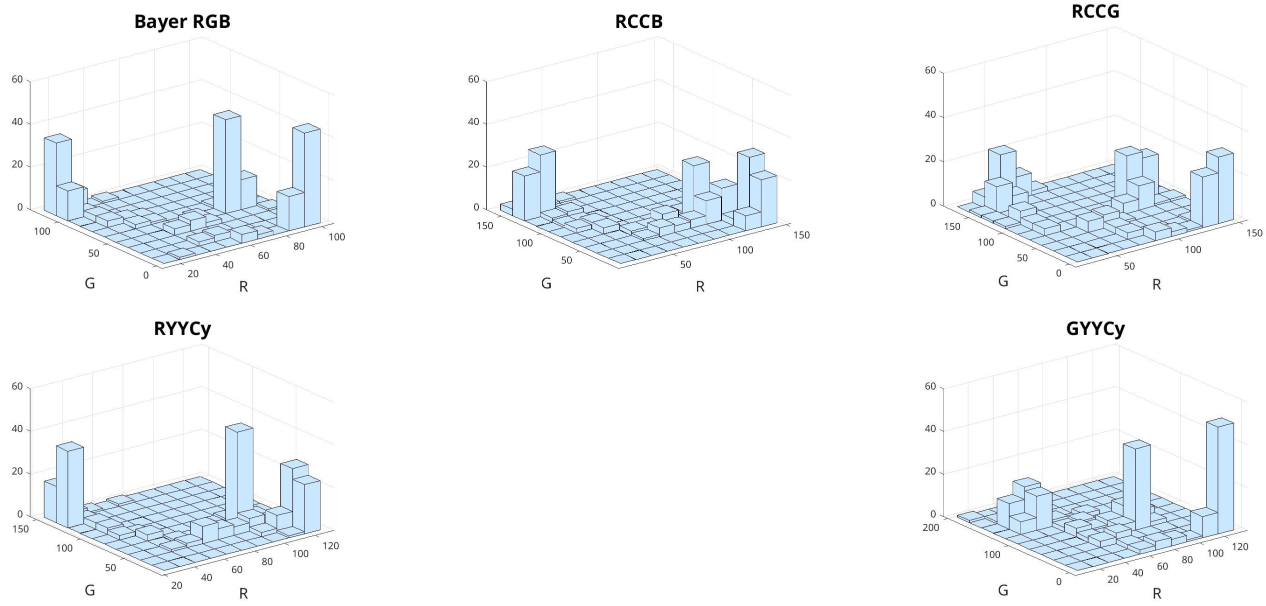
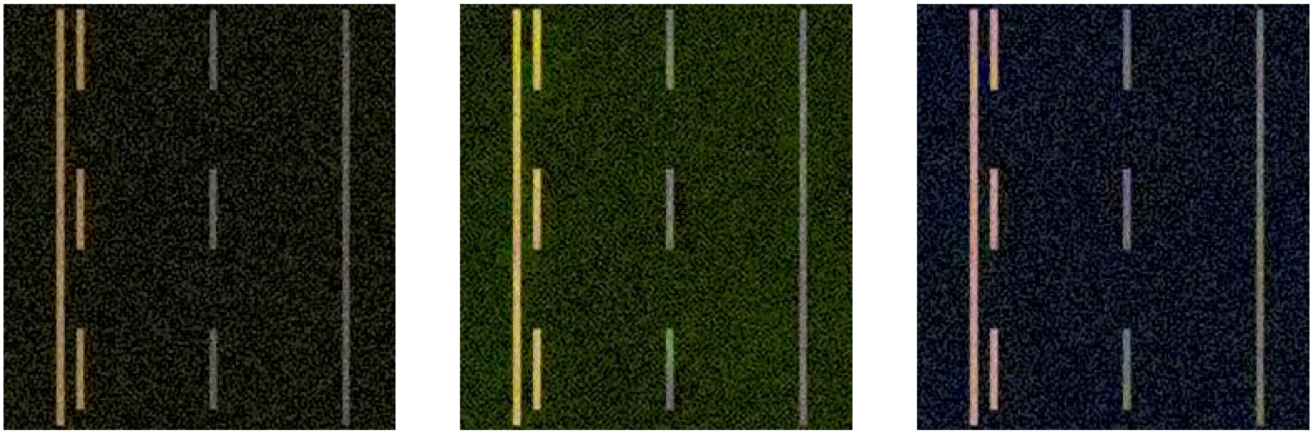


Figure 7: Histograms of LED Traffic Lights, after demosaicking and color correction.



(a) Bayer (b) RCCB (c) RCCG

(d) RYYCy (e) GYYCy

Figure 8: Lane markers in sodium vapor lighting after color correction. A low light, high noise, situation is simulated to stress the color separation.

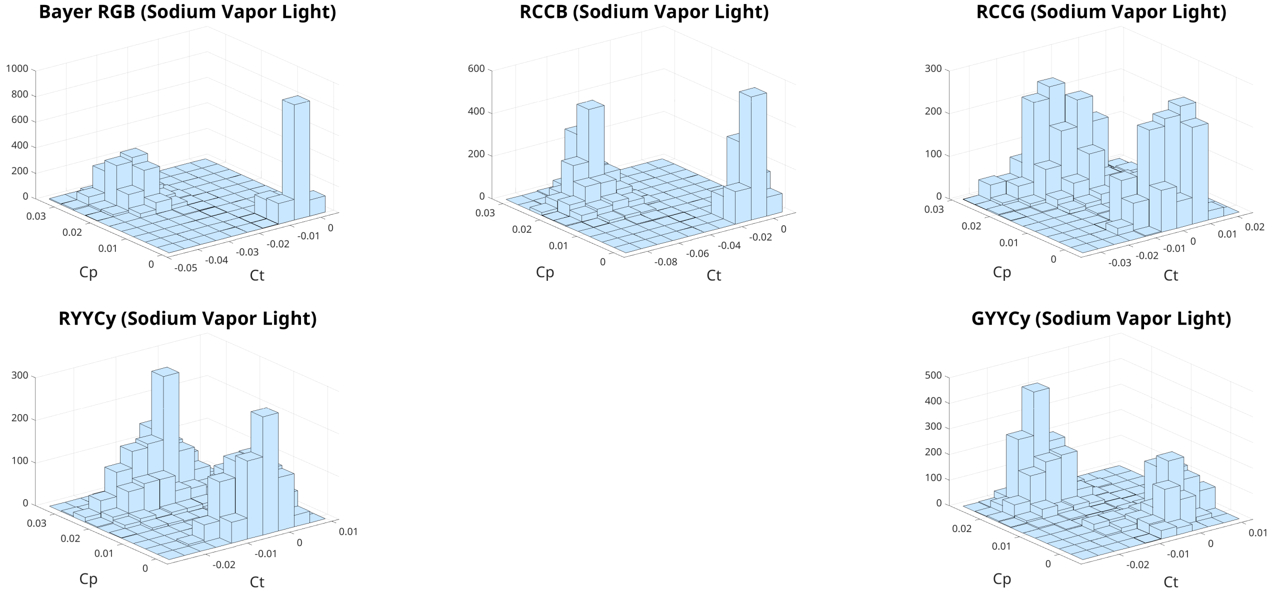


Figure 9: Histograms of lane markers in sodium vapor lighting after color correction.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