https://doi.org/10.2352/CIC.2023.31.1.7

RGB Illuminant Compensation Using Spectral Super-resolution and Weighted Spectral Color Correction

Marco Buzzelli [1]***, Mikhail K. Tchobanou*** [2]***, Raimondo Schettini*** [1]***, Simone Bianco*** [1]

[1] ***Department of Informatics Systems and Communication, University of Milano – Bicocca; Milan 20126, Italy***

[2] ***Moscow Research Center, Huawei Technologies Co. Ltd, Russia***

Abstract

This paper presents a novel approach for spectral illuminant correction in smartphone imaging systems, aiming to improve color accuracy and enhance image quality. The methods introduced include Spectral Super Resolution and Weighted Spectral Color Correction (W-SCC). These techniques leverage the spectral information of both the image and the illuminant to perform effective color correction. Experimental evaluations were conducted using a dataset of 100 synthetic images, whose acquisition is simulated using the transmittance information of a Huawei P50 smartphone camera sensor and an Ambient light Multispectral Sensor (AMS). The results demonstrate the superiority of the proposed methods compared to traditional trichromatic pipelines, achieving significant reductions in colorimetric errors measured in terms of ΔE_{94} *units. The W-SCC technique, in particular, incorporates per-wavelength weight optimization, further enhancing the accuracy of spectral illuminant correction. The presented approaches have valuable applications in various fields, including color analysis, computer vision, and image processing. Future research directions may involve exploring additional optimization techniques and incorporating advanced machine learning algorithms to further advance spectral illuminant correction in smartphone imaging systems.*

Introduction

Color Correction (CC) aims to ensure that the colors in an image appear consistent and accurate, regardless of variations in lighting conditions or the color temperature of the light source, thus enabling reliable color analysis and interpretation of images. This task is particularly important in fields such as digital photography, remote sensing, surveillance, medical imaging, and industrial inspection, where precise color information is essential for accurate object detection, classification, and analysis.

A closely related task is that faced by Color Adaptation Transforms (CATs), i.e. to predict "corresponding colors," that is, a pair of colors that have the same color appearance when viewed under different illuminants. Many CATs have been developed in the last 20 years [1, 2, 3, 4, 5, 6]. Recently, Burns proposed a new CAT [7] that does not operate on the standard von Kries model of adaptation, but it uses a spectral reconstruction technique as an intermediate stage in the process, while still requiring only tristimulus values as inputs. In this work, we investigate if such idea could be implemented in a reliable and efficient way for color correction in smartphones even when filter transmittances are unknown, and the source illuminant RGB tristimulus values are not known but have to be estimated from the image itself.

This work focuses on the development of an innovative spectral illuminant compensation technique. The idea is to recover as accurately as possible the spectral information of both the image and the illuminant, and training a weighted spectral compensation technique (W-SCC) that optimizes a per-wavelength weight matrix to compensate for possible spectral reconstruction errors. Our W-SCC method is therefore independent from the specific illuminant estimation algorithm(s) used, and from the specific spectral reconstruction algorithm adopted.

The proposed approach can also leverage the advances in Ambient-light Multispectral Sensors (AMS), which are hardware modules integrated into certain smartphone models capable of capturing multispectral information of the scene. By combining the AMS data with the illuminant estimates obtained through Auto White Balance (AWB) algorithms, a joint estimation approach is also developed. We show in our experiments that this joint estimation scheme improves the robustness and accuracy of the illuminant estimation, enabling more effective spectral illuminant correction.

The potential applications of the proposed technique are wide-ranging and not limited to digital photography. In industrial inspection tasks, accurate spectral illuminant correction can improve defect detection and material identification, leading to more reliable quality control processes. In remote sensing applications, the precise rendering of colors can enhance the analysis of satellite images for environmental monitoring, land cover classification, and vegetation assessment. Additionally, in surveillance and security systems, accurate spectral illuminant compensation can enhance object recognition and tracking algorithms, improving overall system performance.

Methodology

In this section, we present the methodology employed in our study, which includes the approaches used for spectral illuminant compensation. Our methodology is general purpose, however for the sake of our experiments we focus on a simple algorithm for spectral recovery, and on a sensor-independent algorithm for AWB.

We divide the methodology into three subsections: Scene Illuminant Estimation, Spectral Super Resolution, and Weighted Spectral Color Correction (W-SCC).

Scene Illuminant Estimation

We consider two different inputs for AWB estimation. The first input corresponds to the ground truth illuminant, which represents the color recorded by the camera when the illuminant illuminates a perfect white surface. The second input corresponds to the actual illuminant estimate obtained using an AWB method.

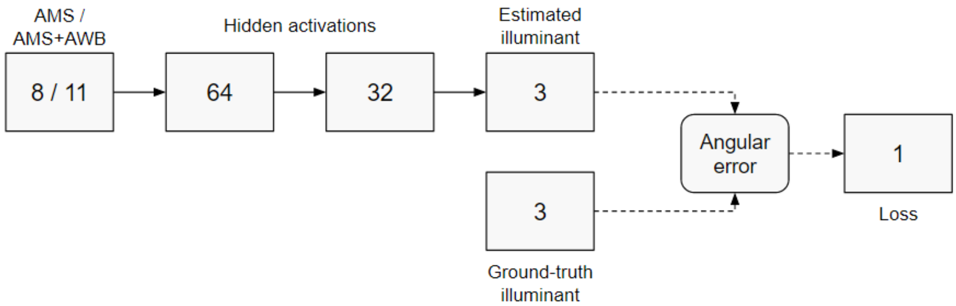

Figure 1. *Neural architecture of the Multi-Layer Perceptron developed for RAW-RGB illuminant estimation, with varying types of input. The numbers reported in the blocks represent the data cardinality.*

Many AWB methods exist in the state of the art, e.g. [8, 9, 10, 11]. To test the effectiveness of our approach, in this work we use a sensor-independent AWB method [12].

We investigate the joint estimation of illuminant spectra using both the AWB estimate and the illuminant estimate provided by the Ambient Multispectral Sensor (AMS) available on the chosen smartphone. We leverage a Multi-Layer Perceptron (MLP) model illustrated in Figure 1 for illuminant estimation from AMS (8 input values) and AWB+AMS (11=8+3 input values) inputs.

Every hidden layer is followed by a Rectifying Linear Unit (ReLU) activation function. The loss is based on the recovery angular error [13] between estimated illuminant $V = (v_R, v_G, v_B)$ and ground truth illuminant $U = (u_R, u_G, u_B)$:

$$err_{rec} = \arccos\left(\frac{U \cdot V}{|U||V|}\right) = \arccos\left(\frac{\sum_i u_i v_i}{\sqrt{\sum_i u_i^2}\sqrt{\sum_i v_i^2}}\right) \quad (1)$$

Spectral Super Resolution

In the first task, referred to as Spectral Super Resolution, we focus on the recovery of spectral illuminant information from RGB illuminant information. Many different methods for spectral super resolution have been proposed in the state of the art [14], ranging from single-pixel reconstruction methods e.g. [15, 16, 17, 18], to full image deep learning-based methods e.g. [12].

In this paper, to prove the effectiveness of the proposed weighted spectral color correction, we employ the pseudo-inverse method [19], which is one of the simplest and most commonly used methods for spectral recovery [20, 21]. This is chosen to prove the effectiveness of our method, since it is general purpose and does not depend on the specific spectral super resolution method used.

Weighted Spectral Color Correction (W-SCC)

Having recovered the spectral information for both the scene pixels and the illuminant, we can use the Chromatic Adaptation Transform by Spectral Reconstruction (CAT-SR) [7] to recover the pixel reflectances to be virtually illuminated with the target illuminant. Using the CAT-SR as it is can lead to sub-optimal results, as we have to consider that we have two possible sources of error, namely the errors in the estimation of the scene illuminant (regardless of the method used) and the errors in the spectral super-resolution. To overcome these limitations we introduce the Weighted Spectral Color Correction (W-SCC), that involves the optimisation of a per-wavelength weight matrix, denoted $W(\lambda)$, which is fixed for all illuminants and input images. The weight matrix is multiplied by the inverse of the spectral illuminant $ILL(\lambda)$, as shown in equation (1):

$$r_{out}(\lambda) = \frac{W(\lambda)}{ILL(\lambda)} r_{in}(\lambda) \quad (2)$$

We optimize the 31 values of the weight matrix $W(\lambda)$ using the average ΔE_{94} error as the target, but other color difference metrics could be used. The optimization process follows a growing approach, starting with the estimation of three equally spaced weights and gradually obtaining the remaining weights through linear interpolation. This iterative optimization is repeated multiple times, estimating 5, 7, 15, and finally all the 31 weights.

Experiments

In this section, we provide details about the experimental setup used for evaluating the performance of the proposed approaches. We also present and analyze the numerical results obtained from the experiments.

Experimental Setup

For our experiments, we used an internal dataset consisting of 100 synthetic spectral images, whose acquisition is simulated using the transmittance information of a Huawei P50 smartphone camera, illuminated by sampling 62 illuminants from several classes (fluorescent, LED, CIE-D series, CIE-A series).

These have been generated using a dataset generation pipeline [22] that uses RAW or sRGB images as a source for the imaged content, and reflectance datasets as a source for spectral reflectance information. The original images were sourced from the INTEL-TAU dataset [23], and the reflectance data from the Ridiqulous dataset [24]. In the experiments the target illuminant considered is the CIE standard illuminant E.

Numerical Results and Analysis

We analyze the error results using several ΔE_{94} statistics and report them in Table 1. The illuminant estimates considered in the experiments include ground truth (both trichromatic and spectral), AWB, AMS, and AMS+AWB.

To provide a comparison with traditional trichromatic pipelines, we compute the ΔE_{94} values when applying a 3×3 color correction matrix along with the classical diagonal Von

Table 1. Colorimetric errors in terms of ΔE_{94} units using different illuminant correction strategies: traditional trichromatic pipeline with diagonal Von Kries correction (rows 1 to 4), spectral illuminant correction with CAT-SR [7] (rows 5 to 9), and Weighted Spectral Color Correction (W-SCC, rows 10 to 14). Results are obtained by using illuminant estimates coming from four different methods: ground truth (both trichromatic or spectral), AWB, AMS and AMS+AWB.

ID	Image	Illuminant	Correction type	MIN	AVG	MED	PRC90	PRC95	PRC99	MAX
1	RAW	GT (RAW)	diag VK	0.11	2.44	2.18	4.10	4.90	6.61	14.34
2	RAW	AWB	diag VK	1.20	6.39	6.23	9.17	10.22	11.93	18.41
3	RAW	AMS	diag VK	0.58	4.87	4.53	7.54	8.28	9.60	16.10
4	RAW	AMS+AWB	diag VK	0.70	4.68	4.52	7.08	7.90	9.31	15.76
5	PINV	GT spectral	CAT-SR	0.98	5.91	5.66	8.68	10.16	11.76	19.29
6	PINV	GT AWB recovered	CAT-SR	0.09	2.90	2.72	4.74	5.49	6.90	15.58
7	PINV	AWB recovered	CAT-SR	0.83	5.11	4.83	7.87	8.99	10.46	18.00
8	PINV	AMS recovered	CAT-SR	0.47	4.71	4.29	7.59	8.16	9.35	16.41
9	PINV	AMS+AWB recovered	CAT-SR	0.51	4.48	4.30	6.92	7.82	8.99	16.37
10	PINV	GT spectral	W-SCC	0.65	4.35	4.10	6.62	7.76	9.15	16.54
11	PINV	GT AWB recovered	W-SCC	0.10	2.58	2.38	4.28	5.05	6.60	14.67
12	PINV	AWB recovered	W-SCC	0.65	4.77	4.52	7.40	8.71	10.50	17.83
13	PINV	AMS recovered	W-SCC	0.48	3.98	3.82	5.88	6.51	7.98	15.61
14	PINV	AMS+AWB recovered	W-SCC	0.55	4.03	3.94	6.10	7.04	8.47	16.10

Kries transformation for illuminant correction. The results obtained with the classical pipeline are reported in rows 1 to 4. Row 1 corresponds to the results obtained when using the ground truth RGB illuminant, while row 2 corresponds to the results obtained using the RGB illuminant estimate provided by AWB. As expected, the best result is achieved when the ground truth illuminant is used, representing the ideal situation. When the AWB-estimated illuminant is used, the classical pipeline yields an average error of 6.39 units.

The spectral illuminant correction [7] and weighted spectral illuminant correction are presented in rows 5 to 9 and rows 10 to 14, respectively.

Upon analyzing the results, we observe that the weighted spectral color correction (W-SCC) consistently outperforms the traditional trichromatic pipeline and the plain spectral illuminant correction approach. W-SCC achieves superior performance in terms of ΔE_{94} error for different illuminant estimates, demonstrating the effectiveness of the weight optimization technique.

By incorporating the AMS data into the joint estimation process, we observe a reduction in error for both the traditional trichromatic pipeline and the spectral approach. Table 1 reports the average errors obtained by the traditional trichromatic pipeline (rows 3 and 4) and the spectral illuminant correction (rows 8 and 9) when using the AMS estimate. We can observe that the spectral illuminant correction achieves the best result, surpassing the performance of the traditional pipeline.

The use of the weighted spectral illuminant correction technique yields improved results compared to the plain spectral illuminant correction approach. The average ΔE_{94} errors obtained with W-SCC for different illuminant estimates are reported in rows 12 to 14. Notably, W-SCC achieves an average error of 4.77 when the illuminant estimated by AWB is used (row 12), 3.98 when the illuminant is estimated with AMS (row 13), and 4.03 when the illuminant is jointly estimated by AMS and AWB (row 14).

Figure 2 provides a graphical representation of the colorimetric errors using different illuminant correction strategies reported in Table 1. The red lines represent the traditional trichromatic pipeline with diagonal Von Kries correction, the blue lines represent the spectral illuminant correction, and the green lines represent the weighted spectral illuminant correction. From the plots, it is evident that the CAT-W approach achieves the best performance across all the considered error statistics. Notably, CAT-W does not seem to benefit significantly from the joint illuminant estimate obtained by AMS+AWB, as it performs best with the illuminant estimate provided by AMS alone. On the other hand, when using the plain CAT-SR approach, the best results are obtained with the joint illuminant estimate by AMS+AWB.

Overall, the experimental results validate the effectiveness and superiority of the proposed approaches, particularly the weighted spectral color correction (W-SCC) technique. The W-SCC method demonstrates improved accuracy in spectral illuminant compensation, showcasing its potential for various industrial applications requiring precise color analysis and interpretation.

Conclusions

In conclusion, we presented innovative approaches for spectral illuminant compensation in smartphone imaging systems. The proposed methods, including Spectral Super Resolution and Weighted Spectral Color Correction (W-SCC), demonstrated improved color accuracy compared to traditional trichromatic pipelines based on diagonal Von Kries correction. The proposed W-SCC technique, in particular, showcased superior performance by incorporating per-wavelength weight optimization. These advancements have significant implications for applications such as color analysis, computer vision, and image processing. Future research can focus on exploring additional optimization techniques and incorporating advanced machine learning algorithms to further enhance spectral illuminant compensation in smartphone imaging systems. Further improvements can be envisioned by considering the availability and future development of advanced methods for spectral recovery and for automatic white bal-

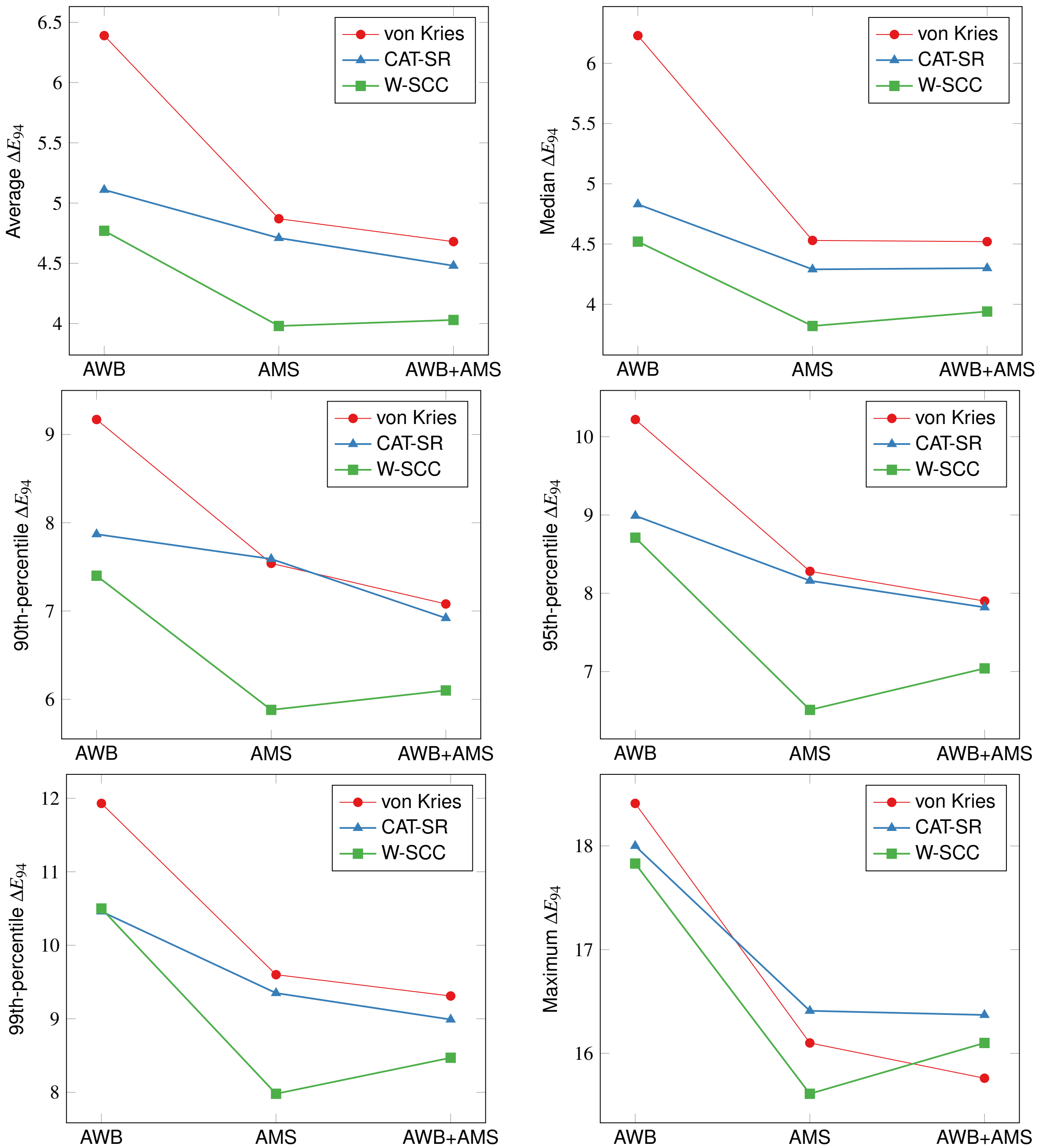

Figure 2. *Graphical representation of the colorimetric errors in terms of ΔE_{94} units using different illuminant correction strategies: traditional trichromatic pipeline with diagonal Von Kries correction (red lines with circle marker), spectral illuminant correction [7] (blue lines with triangle marker), and weighted spectral illuminant correction (green lines with square marker).*

ancing. Finally, additional tests will be conducted on real spectral images.

References

[1] Mark D Fairchild. *Color appearance models*. John Wiley & Sons, 2013.

[2] Changjun Li, M Ronnier Luo, Bryan Rigg, and Robert WG Hunt. Cmc 2000 chromatic adaptation transform: Cmccat2000. *Color Research & Application*, 27(1):49–58, 2002.

[3] Graham D Finlayson and Sabine Süsstrunk. Spectral sharpening and the bradford transform. In *Proc. Color Imaging Symposium (CIS 2000)*, number CONF, pages 236–243, 2000.

[4] Nathan Moroney, Mark Fairchild, Robert Hunt, and Changjun Li. The ciecam02 color appearance model. 2002.

[5] Simone Bianco and Raimondo Schettini. Two new von kries based chromatic adaptation transforms found by numerical optimization. *Color Research & Application*, 35(3):184–192, 2010.

[6] Changjun Li, Zhiqiang Li, Zhifeng Wang, Yang Xu, Ming Ronnier Luo, Guihua Cui, Manuel Melgosa, Michael H Brill, and Michael Pointer. Comprehensive color solutions: Cam16, cat16, and cam16-ucs. *Color Research & Application*, 42(6):703–718, 2017.

[7] Scott A Burns. Chromatic adaptation transform by spectral reconstruction. *Color Research & Application*, 44(5):682–693, 2019.

[8] Arjan Gijsenij, Theo Gevers, and Joost Van De Weijer. Computational color constancy: Survey and experiments. *IEEE transactions on image processing*, 20(9):2475–2489, 2011.

[9] Simone Bianco, Claudio Cusano, and Raimondo Schettini. Color constancy using cnns. In *Proceedings of the IEEE conference on computer vision and pattern recognition workshops*, pages 81–89, 2015.

[10] Yuanming Hu, Baoyuan Wang, and Stephen Lin. Fc4: Fully convolutional color constancy with confidence-weighted pooling. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 4085–4094, 2017.

[11] Jonathan T Barron and Yun-Ta Tsai. Fast fourier color constancy. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 886–894, 2017.

[12] Simone Bianco and Claudio Cusano. Quasi-unsupervised color constancy. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 12212–12221, 2019.

[13] Steven D Hordley and Graham D Finlayson. Reevaluation of color constancy algorithm performance. *JOSA A*, 23(5):1008–1020, 2006.

[14] Boaz Arad, Radu Timofte, Rony Yahel, Nimrod Morag, Amir Bernat, Yuanhao Cai, Jing Lin, Zudi Lin, Haoqian Wang, Yulun Zhang, et al. Ntire 2022 spectral recovery challenge and data set. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 863–881, 2022.

[15] Silvia Zuffi, Simone Santini, and Raimondo Schettini. From color sensor space to feasible reflectance spectra. *IEEE Transactions on Signal Processing*, 56(2):518–531, 2008.

[16] Simone Bianco. Reflectance spectra recovery from tristimulus values by adaptive estimation with metameric shape correction. *JOSA A*, 27(8):1868–1877, 2010.

[17] Jonas Aeschbacher, Jiqing Wu, and Radu Timofte. In defense of shallow learned spectral reconstruction from rgb images. In *Proceedings of the IEEE International Conference on Computer Vision Workshops*, pages 471–479, 2017.

[18] Yi-Tun Lin and Graham D Finlayson. A rehabilitation of pixel-based spectral reconstruction from rgb images. *Sensors*, 23(8):4155, 2023.

[19] Roger Penrose. A generalized inverse for matrices. In *Mathematical proceedings of the Cambridge philosophical society*, volume 51, pages 406–413. Cambridge University Press, 1955.

[20] Yi-Tun Lin and Graham D Finlayson. Evaluating the performance of different cameras for spectral reconstruction. In *Color and Imaging Conference*, volume 30, pages 213–218. Society for Imaging Science and Technology IS&T 7003 Kilworth Lane . . . , 2022.

[21] Mirko Agarla, Simone Bianco, Marco Buzzelli, Luigi Celona, and Raimondo Schettini. Fast-n-squeeze: towards real-time spectral reconstruction from rgb images. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 1132–1139, 2022.

[22] Marco Buzzelli, Mikhail Tchobanou, Raimondo Schettini, and Simone Bianco. A general-purpose pipeline for realistic synthetic multispectral image dataset generation. In *Color Imaging Conference*, 2023.

[23] Firas Laakom, Jenni Raitoharju, Jarno Nikkanen, Alexandros Iosifidis, and Moncef Gabbouj. INTEL TAU: A color constancy dataset. *IEEE Access*, 9:39560–39567, 2021.

[24] Qiu Jueqin. Spectral reflectance database from hyperspectral images - RidiQulous, 2016. (Accessed on 1st April 2022).