Spectral Sensitivity Estimation for Color Camera Calibration

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Abstract

Color accurate acquisition stands as an important topic, especially on certain fields where color fidelity is of strategic importance. Prominent among these applications is that of imaging works of art, on demand for high-quality reproduction. The general purpose is to obtain a representation as closed as we would have seen the original scene. Fundamentals to color imaging are to get color data that are independent face to possible evolution in time of acquisition system parameters like internal sensor responses.

This paper deals with problem of spectral sensitivity function determination. In the first part, a survey with classification of the reconstruction techniques is given. In the second part, we present direct and indirect estimation methods experimental procedures and results obtained for two cameras: a Kodak DCS Pro 14n camera and a PCO 2000 camera by Cooke Corporation. Finally, we describe some metric and perceptual criteria to evaluate spectral response functions reconstruction accuracy.

Introduction

Color accurate acquisition stands as an important topic, especially on certain fields where color fidelity is of strategic importance. Prominent among these applications is that of imaging works of art, on demand for high-quality reproduction. The general purpose is to obtain a representation as closed as we would have seen the original scene. Fundamentals to color imaging are to get color data that are independent face to all possible evolution in time of acquisition system parameters like internal sensor responses.

The acquired image depends on three factors: illumination spectral distribution, object spectral reflectance and imaging system characteristics. Thus, in order to obtain independent device color data, the acquisition system needs to be characterized and calibrated. Device response must be linearized, and dark and white noise have to be measured and removed from the image. Sensor spectral sensitivity curves can then be recovered.

A classification of the reconstruction techniques can be given in three paradigms:

- *Direct estimation*, which is based on multiple spectral acquisition for the inversion of camera model and needs the physical characterization of the object by spectroradiometry or multispectral imaging [1], [2];
- *Indirect reconstruction* or *learning-based reconstruction*, where a calibrated color chart and its image are used to construct an inverse model with various constraints;
- *Reconstruction by interpolation*, where the camera responses are interpolated to find an approximation of the corresponding response function.

This paper deals with the problem of spectral sensitivity function determination. In the first part, a survey with classification of the reconstruction techniques is given. In the second part, we present direct and indirect estimation methods experimental procedures and obtained results for two cameras: a Kodak DCS Pro 14n camera and a PCO 2000 camera by Cooke Corporation. Finally, we describe some metric and perceptual criteria to evaluate spectral response functions reconstruction accuracy.

Spectral Sensitivity Function Determination

The image acquisition process model is known as the interaction of illumination spectral distribution, object spectral reflectance and imaging system characteristics. We denote the linearized sensor response for the k^{th} channel (R, G or B, or monochrome) by C_k, the linearization function by F, the exposure time by e, the sensor noise for the k^{th} channel by b_k, the sensor spectral sensitivity function for the k^{th} channel $S_k(\lambda)$, the spectral repartition of the illumination $I(\lambda)$, the object spectral reflectance $R(\lambda)$ and the spectral range $[\lambda_l - \lambda_h]$. The camera response C_k, for an image pixel, is determined by Eq. 1.

$$C_k = F\left(e \sum_{\lambda=\lambda_b}^{\lambda_h} S_k(\lambda) L(\lambda) \Delta\lambda + b_k \right), \qquad (1)$$

where $L(\lambda) = I(\lambda)R(\lambda)$ is the total incident light on sensor. Finding $S_k(\lambda)$ from C_k can be achieved by various methods. Direct determination and indirect estimations are presented.

Direct Determination

Computing sensor spectral sensitivity function $S_k(\lambda)$ for the k^{th} channel by direct determination consists in multiple spectral acquisition. A white light source passed through a monochromator or some optical filters is acquired and, in parallel, measurement of its spectral distribution is done with a spectroradiometer.

To recover sensitivity functions, we consider camera responses to the measured narrow-band sampling of illumination. Based on Hubel works [3], Vora and Farrell [2] introduced a method using a monochromator. Let n be the number of selected luminous stimuli.

Assuming a narrow-band spectral illumination $L_i(\lambda)$, Eq.1 can be rewritten as Eq. 2.

$$C_k = F\left(\begin{bmatrix} e(1) S_k(\lambda_l) \sum_j L_1(\lambda_l + j\Delta\lambda)\Delta\lambda \\ \vdots \\ e(i) S_k(\lambda_i) \sum_j L_i(\lambda_l + j\Delta\lambda)\Delta\lambda \\ \vdots \\ e(n) S_k(\lambda_n) \sum_j L_n(\lambda_l + j\Delta\lambda)\Delta\lambda \end{bmatrix} + b \right), \qquad (2)$$

where λ_i is the wavelength of the i^{th} incident illumination. Sensibility response can then be estimated as Eq. 3.

$$S_k(\lambda_i) = \frac{F^{-1}(C_i) - b}{e(i) \sum_j L_i(\lambda_l + j\Delta\lambda)\Delta\lambda}, \qquad (3)$$

with C_i the i^{th} component of C_k.

Direct measurements can be very accurate [1], [2], but requires technical instruments, such as a spectroradiometer and a monochromator or some optical interferential filters.

Indirect Estimation

Indirect spectral characterization consists in acquiring chart with known patches spectral reflectance. From the corresponding camera response, spectral sensitivity is recovered by inverting the resulting system, solving the problem with assumption. A common approach for estimation methods is to first compute the linearization function *F*, the exposure time *e* and the noise *b*. Let $C_p = [c_1, c_2, \ldots, c_p]^t$ be the channel response to *p* samples of reflectances $R = [r_1, r_2, \ldots, r_p]$. Eq. 1 can be rewritten as Eq. 4.

$$C_p = R^t S \, , \tag{4}$$

where S $(S=[s(\lambda_1), s(\lambda_2), \ldots, s(\lambda_N)])$, is the spectral sensitivity to recover with N the number of unknown values of this spectral sensitivity vector.

Without Constraint

The system could be obtained by using Moore-Penrose pseudo-inverse method (PI method) [4], which consists in minimising the mean square error, considering no noise. Sensitivity can then be obtained by Eq. 5.

$$S = (RR^t)^{-1} R C_p = (R^t)^- C_p \, , \tag{5}$$

where $(R^t)^-$ denotes the Moore-Penrose pseudo-inverse of (R^t). But, due to noise when considering real sensor, the singular value decomposition of R shows that only few singular values are significant. The estimation will then be very sensitive even to little noise. Barnard [1], Quan [5], Hubel [3], Sharma and Trussell [6] have computed it and confirmed the poor results of this method.

Hardeberg [4] considered this singular value decomposition by solving the system in preserving only principal eigenvectors corresponding to significant singular values (we will then refer to this method as PE estimation). The decomposition of *R* (p x n) is $R^T=UWV^T$, with *U* (p x p) and *V* (n x n) unitary matrices and W (p x n) a diagonal matrix, in which w_i are the singular values, for i = 1… *r* (r<R), with R the rank of the matrix R^t ($R[\leq \min(p,n)]$).

By only taking into account these first *r* singular values, Eq. (5) can be expressed as Eq. 6.

$$S = VW^{(r)-} U^t C_p \tag{6}$$

The *r* values giving the most accurate result are kept.

This solution is less sensitive to noise than simple PI method. But as expressed by Quan [5], great noise forces less eigenvectors to be used. Moreover, the recovered solution can present some negative parts, which do not hold in case of physical sensor. To answer this problem, Hardeberg [4] has proposed to select a set of the most significant reflectance samples: starting with a small number of reflectance samples, chosen according to their spectral variance, more reflectance samples are added in order to maximize the volume defined by the vector space covered by the selected spectra.

These methods show limited results. Thus including some sensor physical constraints to the system resolution is required.

With Constraints

Various constraints can be applied: smoothness, positivity, boundedness or modality.

Pratt and Mancill [7] suggested two methods, Wiener estimation and smoothing estimation. Hubel [3] computed the first one: results seem to be more accurate, but some negative parts in the function can still remain. The second method, based on a smoothing matrix *M*, is given by Eq. 7.

$$S = M^{-1} R (R^t M^{-1} R)^{-1} C_p \, , \tag{7}$$

Another technique has been introduced by Paulus [8], which gave a smooth solution by linear approximation, using a second derivative matrix as smoothing matrix. Nevertheless, results highly depend on applied smoothness weight.

Sharma and Trussell [6] added other constraints with POCS (Projection Onto Convex Set) estimation, which are positivity and boundedness constraints. Based on each of these constraints, a feasible set of the sensitivity functions can be determined and particularly one solution of this set. It consists in an iterative method, and therefore its solution is strongly dependent on the initial chosen point to solve the problem. The solution respects all constraints, but might not be the most accurate one [5].

Based on the same type of resolution, Alsam and Finlayson [9] introduced a method to recover the whole set of feasible functions, by recovering spectral sensitivity with uncertainty. The final result corresponds to the mean of the set, for which the computed variance is indicated.

The quadratic programming solving, proposed by Finlayson, et al [10], takes into account the modality of the retrieved functions. Quan [5] found that applying this method leads to more accurate results.

Quan [5] presented an iterative multiscale basis functions estimation method. Retrieved function given by Eq. 8 is considered as a weighted sum of basis spectral functions, which are chosen as Gaussian functions.

$$S(\lambda) = \sum_{i=1}^{n} \alpha_i B_i(\lambda) \, , \tag{8}$$

where *n*, the number of basis functions, determines the degree of freedom in the model. With this method, obtained functions are closed to the real functions. Finlayson [10] exploited a similar approach with Fourier basis functions. Obtained results show that this method performs well in all cases.

Other estimation techniques have been introduced: according to Quan [5], linear programming approach (König and Herzog [11]) gives close performance from that proposed by Finlayson [10], and approach by parameterizing the sensitivity functions (Thomson and Westland [12]) give less accurate results if no a priori information is available.

However, when considering modality, unimodality or bimodality (often applied) do not always correspond to physical sensor sensitivity functions; thus modality constraint has to be used carefully.

All these estimation techniques lead to variable results: obtained spectral sensitivity will strongly depend on reflectance samples, on applied method, and especially on added constraints. Particularly, some approaches will give very approximate results if constraints, like smoothness or modality, are not used carefully.

Experimental Results

Spectral sensitivities functions estimation results are presented for two cameras: a RGB Kodak DCS Pro 14n camera, with 12 bits of dynamic and a spatial resolution of 4500x3000 pixels; a monochrome PCO 2000 camera by Cooke Corporation, of 14bits of dynamic, and a spatial resolution of 2048x2048 pixels, associated with a CRI Macro-Color RGB liquid crystal filter for the rest of the study.

Direct Determination

First considering direct estimation, Vora and Farrell's approach was the starting point for our own study on both cameras. Instead of using a monochromator, we used optical interferential filters, of 10nm of bandwidth, from 400 to 700nm, for which we characterized the spectral transmittance. Sensitivity curves are recovered, by averaging a central 260x120 pixels area, where a white patch is imaged. The resulting computed spectral sensitivity functions are given in Fig. 1.

With this kind of direct estimation method, positivity will be satisfied for sure, leading to results in agreement with sensor physical characteristics. We also underline the non uni-modality of resulting curves, for both cameras. This remark must be taken into account when applying constraints on estimation sensitivity solving.

Measurements have been done under two different illuminations (Fig. 2). Results denote the illumination spectral distribution importance [4]: from 400 to 420nm, only the noise has been characterized, since the illumination provided no energy for those wavelengths. Thus the monochrome recovered function for PCO camera can not be correctly determined. When using D65 type illumination, better results are obtained for PCO (Fig. 1c), and associating it with the CRI Macro-Color RGB filter, we obtain sensitivities given in Fig. 1d. These last curves for PCO will be used for the rest of this study.

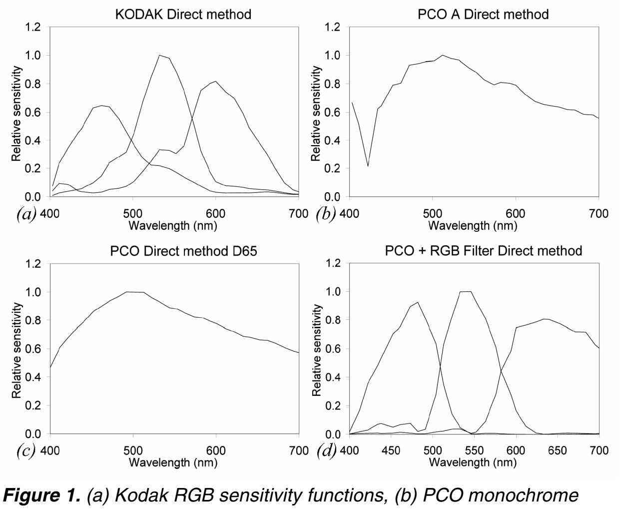

Figure 1. *(a) Kodak RGB sensitivity functions, (b) PCO monochrome sensitivity function with A illumination, (c) monochrome sensitivity of PCO with D65 illumination and (d) color sensitivity of PCO+RGB filter with D65*

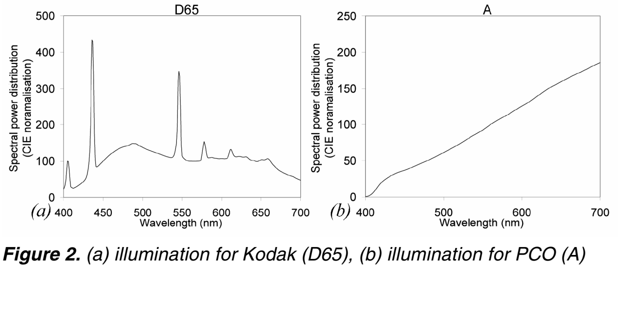

Figure 2. *(a) illumination for Kodak (D65), (b) illumination for PCO (A)*

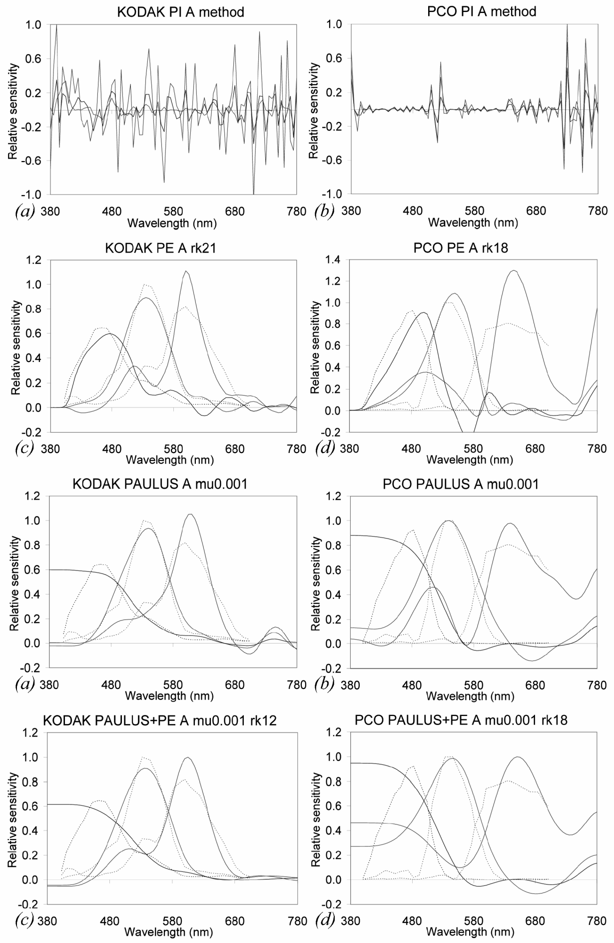

Figure 3. *Estimation with wide band spectra, with results for KODAK camera and PCO camera: (a and b) Pseudo-Inverse, (c and d) PE, (e and f) Paulus and (g and h) Paulus + PE estimations*

Indirect Estimation

Results for some of the presented indirect estimation methods from a great number of wide band spectra patches (from Gretag Macbeth DC Colour Chart) are presented.

In this purpose, patches RGB pixel values have been averaged and their corresponding spectral reflectance measured with a Minolta CS-1000 spectroradiometer, from 380 to 780nm every 5nm.

All potential lighting non-uniformities have been corrected according to luminance profile of the acquisition plan.

We applied PI and PE estimations, Paulus and Paulus + PE methods, on both cameras under various illuminant types, such as illuminants A and D65. Our results underline that, when considering indirect estimation techniques, not only lighting must cover the whole spectral range, but also, no peak must be present in its distribution.

Obtained curves under illuminant A are given in Fig. 3 for both cameras, A being an even illumination.

Results highly depend on applied methods, and show quite different sensitivities.

We compare resulting functions with the ones obtained with direct determination method, as its accuracy has been demonstrated [1], [2].

We can observe the poor result of PI method. All other methods show some negative parts that can be really marked (with PE method for example). Moreover, poorness of our lighting for short wavelengths leads to a low SNR in this spectral range. Thus, when smoothing is used, methods have difficulties to recover curve for these wavelengths, and so specifically for blue channel.

PE method gives the most accurate results (compared to direct measurement method) for Kodak, and each estimation methods fails for PCO sensitivity recovering.

Results Accuracy

In order to validate recovered functions, their accuracy must be qualified, by refining precedent results analysis.

$$F(e(i)\sum S_k(\lambda_j)L_i(\lambda_j)\Delta\lambda_j + b) \qquad (9)$$

Eq. 9 is used to compute response of channel k with estimated spectral sensitivity functions of Kodak and PCO cameras.

Mean and Max RGB errors

From estimated ($Cest_k$) and real ($Creal_k$) RGB values, we computed RGB errors for M patches ($M>P$) (M=522 for PCO and 138 for Kodak). The absolute mean error for each channel k is obtained from Eq. 10.

$$\text{ErrMeanAbs}_k = \frac{100}{dM}\sum_{i=0}^{M-1}\left|Cest_{k,i} - Creal_{k,i}\right|, \qquad (10)$$

where error is expressed as a percentage of maximum sensor dynamic d (2^{16} for PCO and 2^{12} for Kodak). Mean relative error for each channel k is computed by Eq. 11.

$$\text{ErrMeanRel}_k = \frac{100}{M}\sum_{i=0}^{M-1}\frac{\left|Cest_{k,i} - Creal_{k,i}\right|}{Creal_{k,i}}. \qquad (11)$$

For each of those errors, we noted down maximum value for the three channels.

Table 1 gives computed errors for each direct or indirect used method, for each channel and the global three channels. If computed errors are very low, they confirm the validity of results.

As observed previously, the low dimensionality of reflectance spectra leads to deficient results for PI method, when considering RGB errors. Selecting only relevant eigenvectors and smoothing resulting curves (with Paulus and PE methods) greatly improve results accuracy and even give more accurate results for Kodak camera, with errors equivalent to those obtained from direct determination. In a general case, mean relative error is greater for the blue channel, a result which confirms previous analysis.

Repartition of RGB errors

Further analysis can be made to select the most accurate recovered functions. It is the aim of Fig. 4 which compares the predicted values to the real measurements for two tested methods, direct measurement and Paulus methods, for Kodak camera. More the plotted values are dispersed from the theoretical straight line, less accurate the estimation.

Error bar graphs, plotted in Fig. 5, denote the Gaussian distribution of the absolute and relative errors. A narrow Gaussian curve associated with low maximum error values indicates a rather accurate estimation.

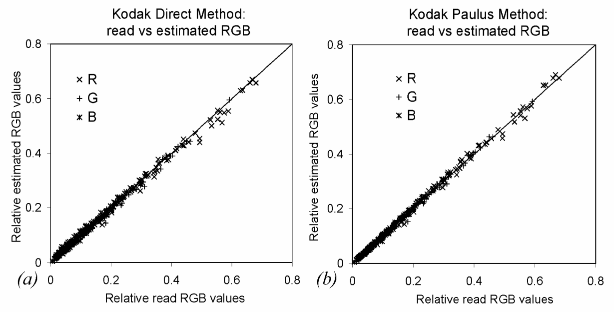

Figure 4. *Estimated RGB values plotted versus read RGB values on sensor, for KODAK sensitivity estimation, by (a) direct measurement method and (b) Paulus method*

Table 1 Error in sensitivity estimation for PCO and KODAK. Errors are calculated by projection of 522 patches for PCO and 138 for KODAK (versus respectively 180 and 90 for estimation).

Errors		Mean				Max
		ΔR	ΔG	ΔB	ΔRGB	ΔRGB
		Absolute (% of max dynamic)				
PCO	Direct method	5.1	4.9	3.2	4.4	25.5(g)
	PI	121	133	91	115	975(g)
	PE	7.7	4.5	3.0	5.1	33(r)
	Paulus	7.4	4.4	2.5	4.8	32(r)
	Paulus+PE	7.9	4.4	2.4	4.9	30(r)
KODAK	Direct method	0.7	0.4	0.2	0.5	3.4(r)
	PI	22.7	22.4	12.2	19.1	71(r)
	PE	0.5	0.5	0.2	0.4	2.3(g)
	Paulus	0.4	0.3	0.2	0.3	1.9(r)
	Paulus+PE	0.4	0.3	0.3	0.3	2.1(r)
		Relative (% of pixel value)				
PCO	Direct method	16.6	21.3	21.6	19.8	80(g)
	PI	350	428	395	391	2089(g)
	PE	21.5	22.6	25.3	23.1	86(g)
	Paulus	21.3	20.4	22.4	21.4	96(g)
	Paulus+PE	22.4	19.7	21.8	21.3	103(r)
KODAK	Direct method	3.3	3.0	3.3	3.2	15.4(b)
	PI	124	141	177	147	1010(b)
	PE	2.9	3.1	3.6	3.2	11.2(r)
	Paulus	2.5	2.9	3.2	2.9	11.0(r)
	Paulus+PE	2.7	2.8	3.3	2.9	11.9(r)

Considering both results from Table 1 and graphs of Fig.4 and Fig.5 can lead us to select the method giving the best results, when observing RGB errors.

Relative error distribution is less narrow than absolute error. This is due to the minimization process applied on absolute rather than relative error. Comparison of two methods can be made on those relative graphics, as relative comparison of color is closer to our own visual color perception. Here, by considering these errors, Paulus method seems to give better sensitivity curves than direct determination method, as repartition is narrower (with greater peaks centered on 0% error). Error standard deviation value of 4.0% against 8.7% confirms this observation. But a complete accuracy analysis has also to take into account retrieved functions plausibility.

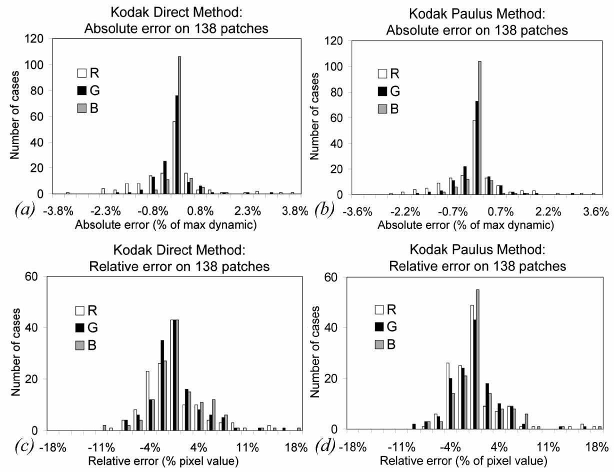

Figure 5. *Repartition of errors on RGB KODAK sensitivity estimation. Absolute and relative error bar graphs, for direct measurement method, respectively (a) and (c), and for Paulus method, respectively (b) and (d)*

Further, a visual reproduction of estimated patches values compared to real measurements can be done. It concerns perceptual error (for example in L*a*b* colorspace) and not RGB error anymore. This perceived variation will depend on observers and graphic reproduction devices such as display or printer.

Conclusion on results

Having computed all these results, different points must be considered in order to give correct verdict:

- Plausibility of sensor sensitivity values (such as respect of positivity, and a maximum modality of two or three),
- Mean and max absolute error for each channel and for the global sensor,
- Mean and max relative error for each channel and for the global sensor,
- Repartition of error: does it follow or not a narrow Gaussian distribution?
- Visualisation of perceptual error, keeping in mind that it will depend on reproduction device.

Regarding all obtained results, for both cameras, direct measurement give the most accurate results.

Discussion

We have briefly reviewed some estimation techniques to recover sensor spectral sensitivity functions. We underlined that some applied constraints like constraints of modality and smoothness require care. Depending on applied methods for two different cameras, we obtained curves satisfying or not these sensor physical constraints. Some direct measurements were also computed and obtained results satisfy plausibility for retrieved sensitivity functions.

For both kinds of methods we have qualified their accuracy, by means of absolute and relative RGB errors computation. Error values and graphical analysis of their repartition lead us to improve our verdict on the accuracy of retrieved sensitivity curves.

Including some constraints for the processed estimation methods could allow a better accuracy, particularly positivity constraint. Another way to improve final curves would be to solve our inverse problem by minimizing relative error rather than absolute error, as human perception of colour is more relative than absolute.

For further works, in order to refine results for method accuracy evaluation, more patches could be used in error computation.

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