https://doi.org/10.2352/CIC.2025.33.1.2

Recovering stable metamers under a varying illumination

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Abstract

It is impossible to recover the actual reflectance that induces a given colour response: as many spectra - called metamers - will integrate to the same response values. For some applications it suffices to recover a good single metamer (satisfying a criterion such that it is the smoothest amongst all metamers). However, when the same surface is viewed under different lights - generating different RGBs - the corresponding reflectances recovered by Smoothest Reflectance estimation (SR) are not all the same. Indeed, there can be a large spectral variation. Recent work has demonstrated that more stable - illuminant insensitive - metamers can be produced by Colour Corrected Smoothest Reflectance estimation (CCSR): where camera RGBs are colour corrected to a canonical reflectance light with respect to which metamers are recovered. In this paper, we examine the relationship between the spectral sensitivities of the camera and both SR and CCSR metamer recovery. Empirically, the variation in recovered metamers for the worst camera for the SR method is found to be 2.5 times larger than the best camera using CCSR. We argue that the stability of metamer recovery in general (for either SR or CCSR) is linked to the extent that accurate colour correction is possible.

Introduction

RGB cameras are pervasive and yet in some application it would be useful to have access to spectral images, such as in medical imaging [1, 2], precision agriculture [3], and quality assessment of food [4, 5, 6]. Thus, there is a sustained interest in estimating spectral information from RGB images, a process sometimes called Spectral Reconstruction.

There are a variety of techniques reported in the literature for Spectral Reconstruction. Assuming that certain *strong* prior statistics about reflectances are known, we can recover spectra analytically in closed form [7]. If the distribution of likely reflectances is a priori known, then maximum likelihood estimation can be used to predict good metamers [8]. With sufficient data, deep learning can be used to predict reflectances from patches of RGBs [9]. Used in isolation, deep learning will typically not find metamers (the recovered spectra do not integrate to the same RGB from which they were estimated) however these networks can easily be adjusted to produce metamers [10]. Arguably, these learning-based techniques are constrained by their heavy reliance on existing datasets and therefore often perform poorly when real reflectances differ from those used for training [11]. Simply put, the recovered reflectance can be - and often is - different from the actual desired reflectance.

This said, there is interest in finding a simple computational method to recover a single 'good' metamer for a given sensor and lighting condition e.g. for modelling corresponding colour data in human vision [12] or upsampling RGB textures to spectral ones in computer graphics [13]. Smoothest reflectance estimation (SR) is a method for reflectance estimation which is founded on the *weak* statistical observation that surface reflectances are typically smooth. By defining the smoothness of a reflectance as the sum of its squared derivatives, an optimisation statement can be created and readily solved using quadratic programming or - via quite a complex algorithm - in closed-form [14, 15].

A weakness of the SR method is perforce that the definition of smoothness depends on the sensor spectral sensitivities and the viewing illuminant. Thus, a different smoothest reflectance is recovered under different lights and the variation in the estimated reflectance spectra can be large. In the top of Figure 1 we show the set of recovered smoothest reflectance recovered for a single reflectance (shown in red) imaged under the 102 lights [16] using a Canon D500 camera [17].

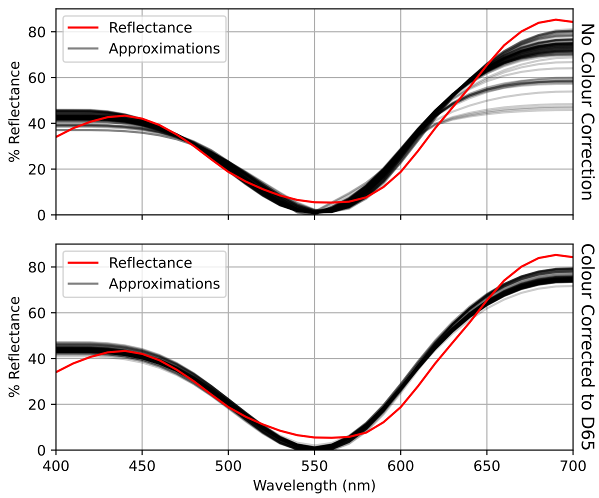

Figure 1. *A reflectance reconstructed under 102 different illuminants. Top shows reconstruction using standard SR, bottom shows reconstruction using CCSR - corrected to the standard illuminant D65 prior to reconstruction. Actual reflectance is shown in red.*

Recently [18], it has been proposed to recover the smoothest reflectance after a colour correction step. The method works in 2 steps. First, the RGB for a given viewing condition (camera and light) is mapped - according to a colour correction transform - to the approximate corresponding RGB under a canonical reference light. Second, the reflectance is estimated with respect to the canonical light. The Colour Corrected Smoothest Reflectance Estimation (CCSR) method halved the variation in reflectance estimation across illumination. See bottom panel of Figure 1.

In this paper, we wish to consider the stability of smoothest metamer estimation across a variety of camera spectral sensitivities. That stability should be camera dependent starts with an elementary proof we present in section 3; that, a camera with 3 narrow-band sensitivities will always recover the same smoothest metamer as illumination varies.

Then, we carry out a large empirical study where - on a cross-validation basis - we examine the stability of metamer recovery for a variety of cameras. We test both the smoothest reflectance estimation and the colour corrected smoothest reflectance estimation methods. For all cameras we find that CCSR returns much more stable metamers (about a 50% reduction in the variation of the recovered metamers).

Importantly, we discover that - for both methods - some cameras return significantly more stable metamers than others. We hypothesise that the stability of metamer recovery is related to how well RGBs can be colour corrected across illumination (and this is true for both the SR and CCSR) methods. Empirically, we find evidence to support this hypothesis.

Next, we present the relevant background material. The proof of stable metamer recovery for narrow-band sensor cameras and our experimental methodology is then discussed. Experimental results are presented and the paper finishes with a short conclusion.

Background

A camera RGB, denoted as a vector $\underline{\rho}$ - componentwise ρ_i ($i \in \{R,G,B\}$) - can be modelled as a function of the light illuminating the scene $E(\lambda)$, the surface's spectral reflectance $S(\lambda)$, and the spectral sensitivities of the camera $R_i(\lambda)$, given λ denotes the wavelength and ω the visible spectrum:

$$\rho_i = \int_{\omega} R_i(\lambda)E(\lambda)S(\lambda)d\lambda \tag{1}$$

By sampling the visible spectrum at N equally spaced wavelengths, this equation can be rewritten in the language of linear algebra:

$$\underline{\rho} = R^T \text{diag}(\underline{e})\underline{s} \tag{2}$$

where R is a $N \times 3$ matrix (red, green, and blue sensitivities comprise the matrix's columns), $\underline{e}$ and $\underline{s}$ are $N \times 1$ discrete sampled measurements of the spectral power distribution of the light and the spectral reflectance.

The smoothness of a reflectance can be defined as the sum of squares of the reflectance's derivative. The derivative can be calculated using a $N \times N$ *operator* matrix ∇ [15, 19]. Smoothness is calculated as:

$$smooth(\underline{s}) = ||\nabla \underline{s}||^2 = \underline{s}^T \nabla^T \nabla \underline{s} \tag{3}$$

Smoothest reflectance estimation can now be formulated as an optimisation problem:

$$\underset{\underline{s}}{\text{argmin}} ||\nabla \underline{s}||^2 \;\; \text{s.t.} \;\; R^T \text{diag}(\underline{e})\underline{s} = \underline{\rho} \;\; \& \;\; \underline{0} \leq \underline{s} \leq \underline{1} \tag{4}$$

Equation (4) is a quadratic objective function subject to linear equality and inequality constraints. This optimisation has a unique global minimum which can be found by quadratic programming [20]. This **uniqueness** property is important. It means we cannot have two metamers that are maximally smooth and integrate to the same target RGB.

A surprising limitation of SR is that it is highly dependent on the illumination. Depending on the viewing illuminant, a different smoothest metamer is recovered. See Figure 1. Recently, in [18], a Colour Corrected Smoothest Reflectance (CCSR) estimation approach was developed. CCSR works in two steps: First, an RGB recorded under a given viewing illuminant is mapped to a fixed canonical reference light. The canonical light in [18] was the D65 standard illuminant [21]. Second, the smoothest reflectance for the mapped RGB for D65 is recovered. This simple procedure can halve the variation of smoothest metamer recovery across illumination.

Intuitively, the better the colour correction the more stable the reflectance recovery. After all, if we mapped the RGB for the same reflectance - viewed under a variety of lights - to exactly the same counterpart under D65 then an identical reflectance would be recovered. Unfortunately, perfect colour correction is not possible - two reflectances may induce identical RGBs under one light but they would be non-identical under a second light - though, year by year, the accuracy of colour correction methods has improved [22, 23, 24, 25, 26].

Method

Let us begin this section by considering the case where smoothest reflection (SR) estimation always returns the same smoothest reflectances as the illuminant changes.

Theorem 1: A camera that has Narrow-band sensitivities will, for the same reflectance, always recover the same smoothest reflectance under different viewing lights.

Lemma 1.1: The smoothest reflectance recovered by a camera does not depend on the camera basis.

We adopt the notation introduced in the Background Section. As before, let the matrix R be the camera sensitivities and RM denotes a change in basis (by a full rank 3×3 linear matrix M). Suppose for a given viewing illuminant the sensor spectral sensitivities R and RM measure the respective RGBs $\underline{\rho}$ and $\underline{\rho}' = M^T \underline{\rho}$. The corresponding smoothest reflectance estimates from these RGBs (and respective sensor bases) are denoted $\underline{s}$ and $\underline{s}'$. Let us assume that $\underline{s} \neq \underline{s}'$ and, without loss of generality we assume that $||\nabla^2 \underline{s}'|| < ||\nabla^2 \underline{s}||$ (one is smoother than the other).

Clearly, $\underline{s}'$ must also induce $\underline{\rho}$ with respect to $\underline{e}$ and R (since $\underline{\rho} = [M^T]^{-1}\underline{\rho}'$). As discussed in the background section, SR estimation has the property that the smoothest reflectance is unique. But, according to this example we have found a reflectance $\underline{s}'$ that is smoother than $\underline{s}$ - both are metamers for $\underline{\rho}$ - but $\underline{s}$ is the unique smoothest reflectance. This cannot be the case. We have a contradiction and, so, the Lemma is proven.

■

Let a Narrow-band camera have 3 Dirac Delta function sensitivities denoted $\delta(\lambda - \lambda_i)$, $i = \{1,2,3\}$, where λ_i denotes the wavelengths where the camera is sensitive to light. In the discrete domain the sensitivity matrix R is zero except for 3 rows (the wavelengths where the camera has sensitivity in one of the sensor channels). In fact, under the Dirac Delta function assumption if p,q,r denote the pth, qth and rth rows of R then $R_{p,q,r} = I$ (the pth, qth and rth row rows extracted from R are the identity matrix). Denoting the 3-vectors with these same rows extracted from the light and a surface as $\underline{e}_{p,q,r}$ and $\underline{s}_{p,q,r}$ it follows that - following from Equation 2 - for the Narrow-band camera, image formation is written as:

$$\underline{\rho} = R^T_{p,q,r} diag(\underline{e}_{p,q,r})\underline{s}_{p,q,r} \tag{5}$$

Because $R^T_{p,q,r} = I$ (I is the 3×3 identity matrix). it follows that we can rewrite Equation 5 as:

$$\underline{\rho} = diag(\underline{e}_{p,q,r}) R^T_{p,q,r}\underline{s}_{p,q,r} \tag{6}$$

where we note this equation is independent of reflectance. Image formation for a second light $\underline{e}'$ is written as:

$$\underline{\rho}' = diag(\underline{e}'_{p,q,r}) R^T_{p,q,r}\underline{s}_{p,q,r} \tag{7}$$

Referring back to the Lemma we could set:

$$M^T = diag(\underline{e}'_{p,q,r}) diag(\underline{e}_{p,q,r})^{-1} \tag{8}$$

That is, a change in illumination is equivalent to a change of sensor basis. From the Lemma we know that the same smoothest reflectance is recovered with respect to a change of sensor basis. This completes the proof. A narrow-band sensor will always recover the same smoothest reflectance under different lights.

■

Now, we will carry out a systematic review of how Colour Corrected Smoothest Reflectance (CCSR) estimation improves standard smoothest reflectance estimation (SR) as both the illuminant and camera spectral sensitivities vary. If we can - to a good approximation - always colour correct to the same colours under a canonical light then we expect more stable smoothest reflectance metamers to be recovered.

The SR and CCSR methods are tested for 28 different camera spectral sensitivities [17] and with respect to 102 illuminants [16]. The canonical illuminant for colour correction was set to the CIE standard D65 [21].

We examine spectral reflectance estimation on a cross-validation basis. Here we use 4 reflectance datasets. Each reflectance dataset is used as a test set (with the remain 3 used to solve for the colour correction matrix). The reflectance datasets we use are:

- **MUN** contains reflectances from the Munsell Book of Colour, Matte Edition [27].
- **OBJ** contains reflectances from a variety of sources including both man-made surfaces like fabrics, and natural surfaces like hair and vegetation [28].
- **DUP** contains DuPoint Colour Sampler reflectances [28].
- **NAT** contains assorted foliage and flowers [29].

For the kth camera, ith illuminant and jth reflectance, we denote an estimated smoothest (SR) reflectance - from the corresponding RGB $\underline{\rho}^{i,j,k}$ - as $\underline{s}^{SR}_{i,j,k}$ and the mean of a reflectance reconstructed under all lights as $\underline{\mu}^{SR}_{j,k}$ We can then calculate a per reflectance percentage error (where 0% indicates the same reflectance is recovered regardless of illuminant) using:

$$\%\text{Error}^{SR}_{i,j,k} = \frac{||\underline{s}^{SR}_{i,j,k} - \underline{\mu}^{SR}_{j,k}||}{||\underline{\mu}^{SR}_{j,k}||} \tag{9}$$

For the CCSR method we, analogously, denote the recovered reflectance as $\underline{s}^{CC}_{i,j,k}$. Here the % error is written as:

$$\%\text{Error}^{CC}_{i,j,k} = \frac{||\underline{s}^{CC}_{i,j,k} - \underline{\mu}^{CC}_{j,k}||}{||\underline{\mu}^{CC}_{j,k}||} \tag{10}$$

The %Error for the kth camera - where either the SR or CCSR recovery algorithm is used - for all lights and surfaces is equal to:

$$\%\text{Error}^{Alg}_{k} = \frac{1}{n}\sum_i\sum_j \%\text{Error}^{Alg}_{i,j,k}\ ,\ Alg \in \{SR, CC\} \tag{11}$$

n is the number of surfaces multiplied by the number of lights. Note this is the same for both methods.

With respect to the CCSR algorithm, we made the hypothesis that we expect that the % error in estimation will be small if colour correction works well. And, this intuition was formalised by the proof that a camera with Delta function sensitivities would have a 0% estimation error (for the same actual reflectance we would always recover the same smoothest metamer). Now, we wish to evaluate whether this intuition holds empirically.

For the kth camera, let us denote a $3 \times m$ (m reflectances) of RGBs under the ith viewing and canonical lights as, respectively, $P^{i,k}$ and $P^{c,k}$. The percentage root mean squared colour correction error for the kth camera, where a linear correction matrix is used is calculated as:

$$\%\text{CCError}_k = \frac{1}{102}\sum_i \frac{||P^{i,c,k} - P^{c,k}||}{||P^{c,k}||} \tag{12}$$

where $P^{i,c,k} = M^{i,c,k}P^{i,k}$ (the colour correction transform $M^{i,c,k}$ maps RGBs for the kth camera and the ith light to the canonical light c). We average over all 102 lights.

Of course, other colour correction algorithms can be used including 2nd, 3rd, and 4th degree polynomial and root-polynomial colour corrections, see [22]. In this case $P^{i,c,k}$ denotes the RGBs viewed under illuminant i corrected - using one of these methods - to the canonical light c for the kth camera.

We wish to quantify how correlated a given camera's average % recovery error is to the the colour correction error. To calculate

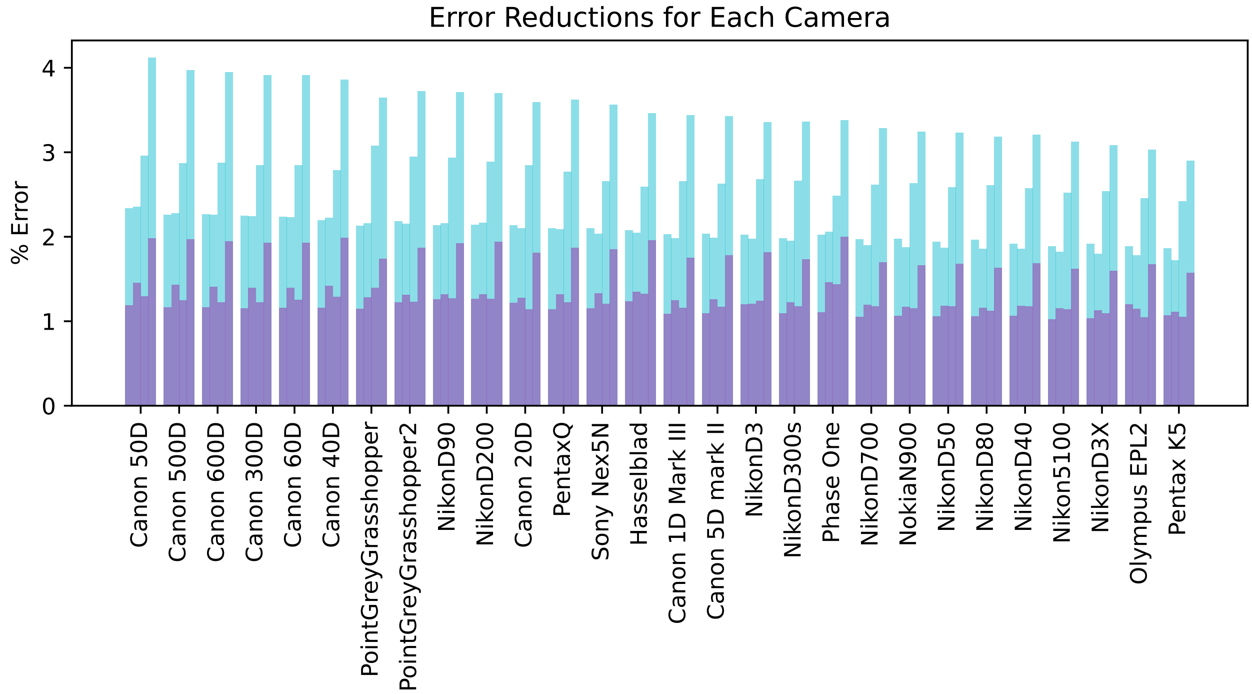

Figure 2. *Full results when testing on all cameras. Each bar's overall height corresponds to the % error without using colour correction, the darker region shows the error when using CCSR with the optimal colour correction technique for that camera and dataset. Each camera labels four bars, these correspond to the 4 testing reflectance datasets:* ***MUN***, ***OBJ***, ***DUP***, *and* ***NAT***.

correlations between two variables the Pearson correlation coefficient is used. Given two vectors X and Y, with means $\bar{X}$ and $\bar{Y}$, the correlation coefficient is calculated as:

$$Corr(X,Y) = \frac{\sum_k (X_k - \bar{X})(Y_k - \bar{Y})}{\sqrt{\sum_k (X_k - \bar{X})^2 \sum_i (Y_k - \bar{Y})^2}} \tag{13}$$

In the context of this paper, $X_k = \%\text{Error}_k^{Alg}$ and $Y_k = \%\text{CCError}_k$. We are also interested in how well SR correlates with CCSR (in this case $X_k = \%\text{Error}_k^{SR}$ and $Y_k = \%\text{Error}_k^{CC}$). Correlation coefficients with larger magnitudes indicate stronger correlations, with 1 and -1 indicating the strongest and weakest correlations whilst a value of 0 indicates no correlation [30].

Results and Discussion

RGB values were generated using every reflectance in each dataset under all 102 illuminants and using all 28 cameras. We then estimated the reflectances with SR and seven variants of CCSR (using linear; 2nd, 3rd, and 4th degree polynomial; and root-polynomial colour corrections). The per camera best colour correction transform (the one that resulted in the least CCSR recovery error) is recorded in Table 1.

Results are shown using the SR and CCSR methods for each camera and dataset in Figure 2. The SR results are shown in light blue and the CCSR results are shown in purple. Each camera has 4 performance bars (corresponding to the 4 test datasets). Comparing SR to CCSR, we found that CCSR had lower error - the reflectance recovery was much more stable - for all cameras using all datasets. Clearly, for all test reflectance sets and all cameras, the CCSR method returns more stable smoothest metamers. Comparing the worst performing camera (Canon D50) for the SR method to the best (Pentax K5) and the CCSR method - and averaging over the 4 testing reflectance sets - we find that %Error for the D50 camera is 2.5 larger than for CCSR using the K5 camera.

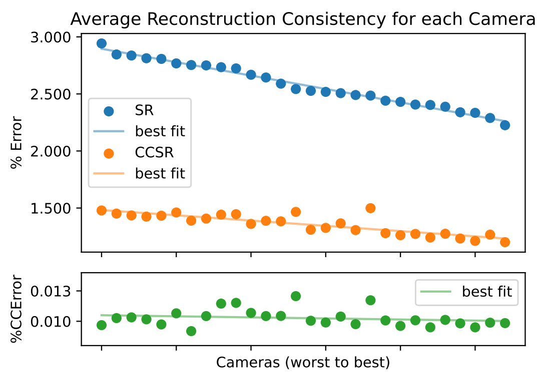

Figure 3. *Error for each camera (averaged across all datasets) with and without colour correction (above). Colour correction error for those cameras (below). Cameras are ordered from least to most consistent when not using correction (the same order as in Figure 2).*

In Figure 3, the mean recovery error (averaged across all 4 reflectance testing sets) over the 28 cameras is show as blue dots. This is shown in descending sorted order - for smoothest reflectance (SR) recovery stability. The order is the same as shown in Figure 2. The corresponding % error for the best CCSR method is shown in orange. In the bottom panel, we show the mean colour correction error, in green, for each camera (in the same sort order).

Table 1: Optimal colour correction method for each camera.

Correction Type	Cameras
4th Degree Polynomial Colour Correction	Canon 1D Mark III, NikonD3X, NikonD40, NikonD50, NikonD80, NikonD300s, NikonD700, Nikon5100, NokiaN900, Olympus EPL2, Pentax K5, Sony Nex5N, PointGreyGrasshopper
2nd Degree Root-Polynomial Colour Correction	Phase One
3rd Degree Root-Polynomial Colour Correction	Canon 5D mark II, Canon 20D, Canon 40D, Canon 50D, Canon 60D, Canon 300D, Canon 500D, Canon 600D, NikonD3, NikonD90, NikonD200, PentaxQ, Hasselblad, PointGreyGrasshopper2

Now, we calculate the correlation coefficient between the per camera % estimation error for SR and CCSR (blue with orange dots). The Pearson correlation coefficient between the error values before and after correction is 0.84, indicating a strong correlation [30].

CCSR error also moderately correlates with colour correction error (orange versus green dots): correlation coefficient of 0.61. Despite this clear correlation, there are some exceptions. The five cameras with the worst SR error values (all Canon cameras) clearly do not fit the overall trend, having very low colour correction error but high variability in the recovered SR reflectances. Removing these 5 cameras from the correlation computation we find that there is now a strong correlation with a coefficient of 0.79.

Correlation between baseline SR error and the colour correction error (blue and green dots) is weaker. Again, excluding the initial five outliers produces a moderate correlation coefficient of 0.42, though this is reduced to a weak correlation of 0.20 when included. This is an interesting result. It teaches that the colour correctability alone - as a property of a given camera - does not imply that there will be stable smoothest reflectance estimation across illumination. Rather, one needs to actually colour correct to the canonical light in order to achieve more stable smoothest metamer recovery.

Conclusion

One way to recover a reflectance from an RGB - for a known camera and viewing illuminant - is to optimise to find the smoothest reflectance (that integrates to the given RGB). However, this definition of smoothest reflectance (SR) recovery is linked to both the camera and viewing illuminant. As the illumination changes the recovered smoothest reflectance can and does vary significantly. Recently, this led to a new algorithm for smoothest reflectance recovery where, in a first step, camera RGBs are colour corrected to a canonical light and then, in a second step, smoothest reflectances are recovered for the canonical light. Colour Corrected Smoothest Reflectance (CCSR) recovery halved the variability in smoothest reflectance metamers.

In this paper we made two main contributions. First, by appealing to intuition and also by providing a Theorem and proof about cameras with Narrow-band sensitivities we argue that the better we are able to colour correct to a canonical light the more stable the smoothest reflectances will be. Second, we carried out a large empirical study involving 28 cameras, 102 lights and 4 reflectance data sets - combined, comprising well over 1000 reflectances - to investigate how well SR and CCSR methods work and whether the efficacy of either methods is linked with the colour correctability of a given camera.

In summary, we found that CCSR always recovers smoothest reflectance metamers that are much more stable as the illumination varies. The variation is about half of SR. Moreover, the combination of camera and algorithm can lead to dramatically different ranges of smoothest metamers. The error (variability) of the worst camera for the SR algorithm is 2.5 times larger than the variability of the best algorithm running the CCSR algorithm. Further, we found that the CCSR recover performance was quite strongly correlated to how well a colour correction method could discount the illuminant (map to the canonical).

Future work includes investigation of the narrow-bandedness of camera sensitivity curves, an evaluation of how this relates to stable metamer prediction and colour correction error, and an investigation into how this can be used to improve stability in colour corrected smoothest reflectance estimation.

Acknowledgments

This work was supported by the Engineering and Physical Sciences Research Council (EPSRC) AgriFoRwArdS CDT award EP/S023917/1 and the EPSRC grant EP/S028730/1.

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