Comparing Colour Camera Sensors Using Metamer Mismatch Indices

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ABSTRACT

A new method of evaluating the colorimetric accuracy of a color camera is proposed that is based on the size (appropriately normalized) of the metamer mismatch volume induced by a change of 'observer' from camera to human eye and vice-versa. The degree of metamer mismatching indicates the range in the discrepancy of the colour signals that can arise and as such is a more well-founded measure of colorimetric accuracy than traditional spectral-based measures such as the root mean squared difference in fit between the camera and eye's sensitivity functions.

1. INTRODUCTION

It is well known that only a colour camera that satisfies the "Luther condition" (Luther 1927) can provide colorimetrically accurate colour images. Of course, colorimetric accuracy is only one issue of concern, and not necessarily the most important one, in terms of overall image quality. However, there are many situations—for example, dermatological imaging or paint and dye applications—in which it would be desirable to have a camera act as an imaging colorimeter. The Luther condition requires the camera sensitivity functions and the human eye's sensitivity functions to be within a linear transformation of one another. The problem with this condition is that it is all or none. If there is not an exact match then how is the discrepancy to be measured?

We address this question using the volume metamer mismatch index (VMMI) (Logvinenko 2014b) and compare the indices obtained for the sensitivity functions of the 28 digital cameras Jiang et al. (Jiang 2013) measured. The VMMI is a measure of the amount of metamer mismatching that can occur between two different observers for a given light. In this paper, one observer is fixed and defined by the human cone fundamentals; the other observer is defined by the spectral response functions of the colour camera being evaluated. Metamer mismatching for a pair of observers (sometimes called 'observer metamerism') refers to the fact two lights that induce an identical sensor response in one observer (i.e., match), may induce non-identical sensor responses in the second observer. The set of all possible such non-identical responses forms a convex volume in colour space referred to as the metamer mismatch volume.

The intuition behind using the degree of metamer mismatching in evaluating the colour fidelity of a digital camera is that if two lights match for the human observer, then it follows that ideally the camera should produce an identical RGB response to the two lights. If it does not, or if it produces identical RGB responses to lights that the human observer sees as distinct, then there cannot exist a one-to-one mapping between camera response and perceived colour. The greater the degree of metamer mismatching, the greater the ambiguity in the mapping between camera response and perceived colour, and hence, the less colorimetrically accurate the camera will be.

2. CAMERA VOLUME METAMER MISMATCH INDEX (CVMMI)

The Camera Volume Metamer Mismatch Index (CVMMI) is a measure of the amount of metamer mismatch between a particular camera sensor and the reference human observer. The CVMMI is a particular case of the VMMI in which: (*i*) the spectral response functions (Figure 1) of the reference human observer are those defined by the Govardovskii et al. model of photopigment responsivity (Govardovskii 2000) with peak photopigment optical density of 0.3 and peak absorbances of 430nm, 530nm, 560nm; and (*ii*) the metamer mismatch volumes are computed for lights that are for the first observer metameric to the equal-energy illuminant.

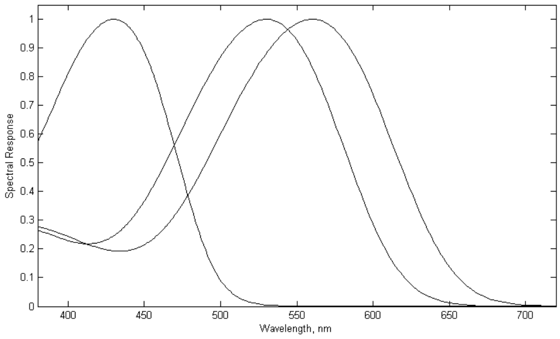

Figure 1: The relative spectral response functions for the reference human observer based on the Govardovskii et al. model of the cone sensitivities.

2.1 Calculating the Metamer Mismatch Volume

The metamer mismatch volume (MMV) for a given colour signal (i.e., XYZ, LMS or RGB, depending on the colour sensors used) recorded by the first observer in response to a given light is the set of all colour signals arising from lights that are metameric to the given colour signal that could possibly be recorded by the second observer. Logvinenko (Logvinenko 2014b) suggests that the size of the MMV can be measured in various ways, such as terms of its ‘diameter’, its area when projected into a 2D chromaticity space, or its three-dimensional volume. In this paper, we choose to use the cube root of its three-dimensional volume.

We calculate the MMV for the second observer given colour signal, Ψ_1, of the first observer using the new method Logvinenko describes (Logvinenko 2014b). This method is based on randomly choosing a set of 3 monochromatic lights and then finding a linear combination of the chosen lights that is metameric to Ψ_1. The response, Ψ_2, of the second observer to this linear combination provides a point in the MMV. Since this computation is fast, it can be repeated thousands of times with different sets of monochromatic lights thereby leading to lots of points on the boundary of the MMV. The convex hull of this set of these points provides a good approximation to the MMV.

2.2 Volume Metamer Mismatch index

While the volume of the MMV provides a measure of the amount of metamer mismatching, it varies in proportion to light intensity and to any linear transformation of the spectral sensitivity functions. To obtain a measure that is unaffected by these factors, Logvinenko (Logvinenko 2014b) introduces the Volume Metamer Mismatch Index (VMMI). The VMMI is defined as ratio of the volume of the MMV relative to the volume of the convex hull of the spectral curve for the second observer (see Eq. 8 of Logvinenko 2014b for the formal definition). Since light intensity affects both volumes equally, as does a linear transformation of the sensitivity functions, the ratio remains unaffected.

The VMMI for the case of the reference human observer to a camera as the second observer provides a measure of how well or poorly the given camera is at representing colours as seen by the human observer. A high VMMI means that lights that look the same to the human observer can end up with significantly different RGB outputs from the camera. For the reverse case, that of the VMMI for a change from camera as the first observer to human as the second observer, the VMMI gives a measure of how well the camera preserves differences seen by the human eye. A high camera-human VMMI indicates that two lights that look very different to the human eye may be indistinguishable to the camera.

The VMMI can be computed for any colour signal Ψ_1 of the first observer in response to a light. In terms of using the VMMI as a measure of the colour fidelity of cameras, however, we define Ψ_1 to be the colour signal of the first observer in response to the equal-energy spectrum. This single case is taken as being representative of the degree of metamer mismatching for all spectra since the color signal corresponding to the equal-energy case has the largest VMMI. At the other extreme, is the colour signal of monochromatic light, for which there are no metamers.

It is possible for a camera to have a low human-camera VMMI (for colour signal of equal-energy spectrum) while having a high camera-human VMMI, and vice versa. For a camera to be colorimetrically accurate, both must be low. Therefore, we define the Camera Sensor Metamer Mismatch Index (CSMMI) as the average of the two.

2.3 Restricting the lights

Lights leading to colour signals on the boundary of the MMV have spectra that are non-zero at only three wavelengths. Such lights are not very representative of lights that are actually encountered by cameras in practice, although imaging a laser-based display would be a clear exception. The problem with evaluating the CSMMI for monochromatic lights is that a small difference in the camera response at a particular wavelength can lead to a high degree of potential metamer mismatching. The volume of the MMV correctly represents the range of possible responses, but this may not be what is desired in practice where monochromatic lights rarely arise, and also where the camera's sensor sensitivity functions may not have been measured all that precisely at every wavelength.

To avoid the problem of small differences in the sensor response functions leading to large differences in the CSMMI, we replace the monochromatic lights with lights having a Gaussian-shaped spectrum. Metamers are then found using linear combinations of three such lights with peaks centered at three different wavelengths. Since the set of lights is being restricted, the resulting MMVs are smaller and strictly inside the theoretical MMVs based on linear combinations of 3 monochromatic lights.

Figure 2 shows examples of the light spectra formed as a linear combination of Gaussian spectra with standard deviations of either σ=25 or σ=50. At σ=25, the Gaussian spectra are more similar the peaks in LED spectra. The spectra formed as a linear combination of three Gaussian spectra with σ=50 are closer to typical broadband light sources. We denote the CSMMI indices computed using Gaussian spectra of σ=25 and σ=50 CSMMI25 and CSMMI50, respectively.

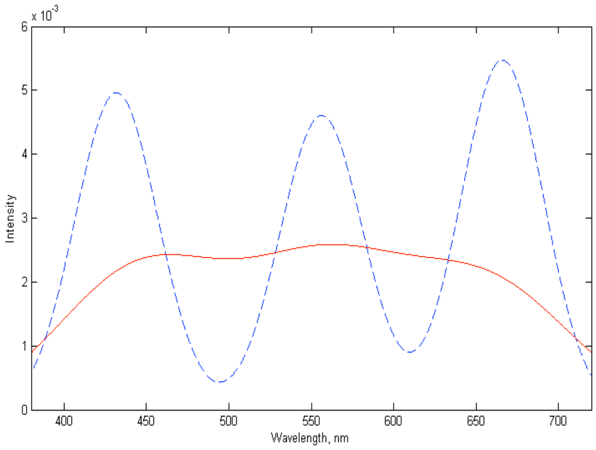

Figure 2: Two spectra that are metameric to the equal-energy spectrum formed as linear combinations of Gaussian lights of standard deviation σ=25 (dashed blue curve) and σ=50 (solid red curve).

3. RESULTS AND DISCUSSION

We computed the CSMMI25 and CSMMI50 measures for the sensor sensitivity functions of the 28 cameras measured by Jian et al. (Jiang 2013). The computation was based on finding 10,000 metameric lights as described above.

Jiang et al. rank the cameras in terms of two measures. The first is the departure from the Luther condition as measured in terms of the Root Mean Squared error in the best linear fit of the camera sensitivites to the CIE-1931 2-degree color matching functions. The second measure is the average CIEDE00 color difference taken over the 1269 Munsell reflectance spectra (Parkkinen 1989) illuminated by CIE D65 and measured between the transformed camera coordinates (i.e., best camera estimate of XYZ) and the true CIE XYZ. The RMS difference is a general measure, but using the average CIEDE00 over a set of reflectances is not. The problem is not only that the set of reflectances is limited, but that the reflectances are not lights. A general measure of camera colour fidelity must include the space of all lights, not just the space of lights reflected from surfaces under D65. In any case, Jiang et al. show that there is only a very limited correlation between the rankings that the two measures provide.

Figure 3 plots the RMS and CSMMI50 measures for the 28 cameras sorted in order of increasing CSMMI50. The two measures follow the same general trend, but there are significant disagreements between the two measures. The fact that the RMS measure can sometimes be small while the CSMMI is large is an indication of the problem with using the similarity of the camera and eye spectral sensitivity functions as a measure of colour fidelity since the CSMMI reveals that relative small differences as measured in terms of RMS can in fact lead to large colour differences between the camera and eye.

Of course, the CSMMI25 and CSMMI50 can be expected to be very correlated. Figure 4 shows that the two indices track one another closely with a few exceptions. Camera 6, for example, has a higher relative CSMMI25 than CSMMI50. This indicates that the colour fidelity of that camera will be poorer for lights with spectra having narrowband peaks than lights with strictly broadband spectra.

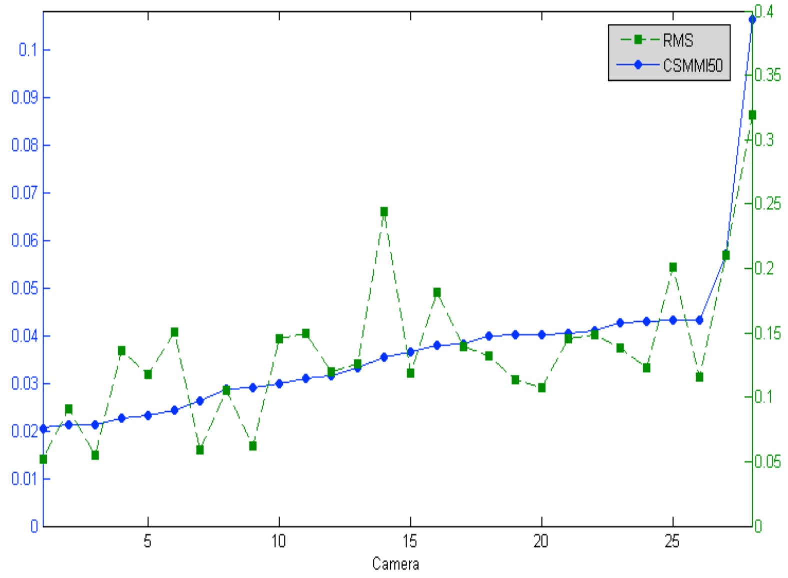

Figure 3: The RMS (dashed green) and CSMMI50 (solid blue) measures for each of the 28 cameras with the results sorted in left−to−right order in terms increasing CSMMI50. Left axis CSMMI50 index. Right axis RMS value.

Note that since the MMVs for the σ=50 lights are significantly smaller than the MMVs of the σ=25 lights the range of the CSMMI50 indices is always smaller than that of the CSMMI20 indices.

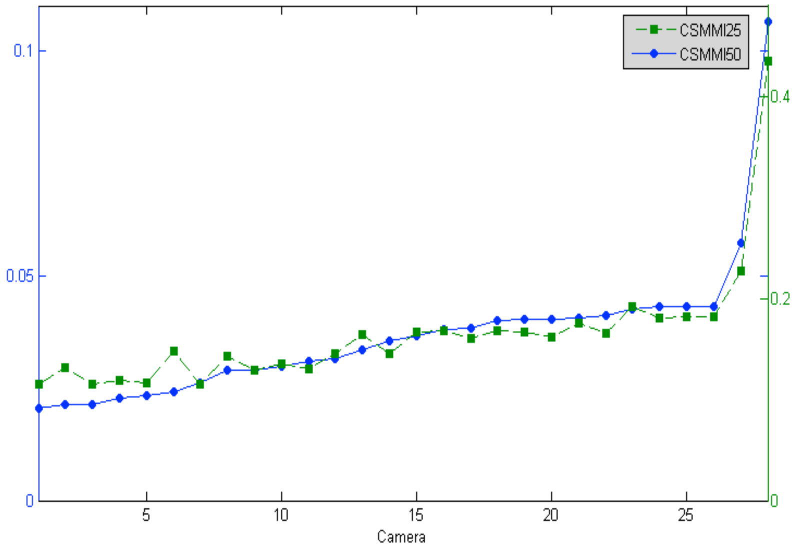

Figure 4: Comparison of the CSMMI50 and CSMMI25 indices. Cameras are ordered in terms of increasing CSMMI50. The relative scale of the two plots has been adjusted so that they overlap for comparison.

4. CONCLUSION

Digital colour cameras do not generally satisfy the Luther condition and therefore will not produce images that are entirely colorimetrically accurate. The Luther condition is all or none. To compare the colorimetric accuracy of cameras requires a different measure, for which the RMS error in the best linear fit of the camera sensitivity functions to the human cones is often used. As an alternative, we propose a new measure, the camera sensor metamer mismatch index (CSMMI), based on Logvinenko's (Logvinenko 2014b) volume metamer mismatch index, which in turn is based on the amount of metamer mismatching that is induced by a change from the eye's sensitivity functions to a camera's and vice-versa. As such, it provides a principled measure of the colorimetric accuracy of a camera.

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