Rethinking the White Point

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Introduction

In this talk we will discuss *calibration transforms* that map the *XYZ* values generated by the same surface under different illuminants. We use the phrase calibration transforms to distinguish between analyses based on the physical properties of surfaces and illuminants, and to distinguish them from *appearance transforms* based on measurements of color appearance. Calibration transforms describe how the *XYZ* coordinates measured for a surface change with illumination. Appearance transforms describe how the *XYZ* coordinates of a particular appearance change with illumination. The change in *XYZ* values due to calibration and appearance transforms do not generally coincide.

Calibration and appearance transforms serve different and useful functions in color management systems. Calibration transforms can be used to correct the device-independent color descriptors of surfaces that have been calibrated for one illuminant but will be rendered under a different illuminant. These calculations play an important role in device calibration. Appearance transforms share a similar computational structure, but they have a different goal and are not *XYZ* matches.

One step in performing automated calibration transforms is to estimate the illuminant spectral power distribution (SPD). Performing the transform is much simpler if one can estimate the illuminant SPD from a three-sensor device, rather than using a spectroradiometer.

We first analyze an illuminant estimation method based on using linear models of the illuminant SPD. This solution is taken from the color constancy literature and assumes very little or no information about the objects in the image.

In many practical applications the need for accurate calibration transforms outweighs the advantages of algorithms based on little or no information about the surfaces and illuminants in a scene. In this paper we describe how a measurement of a single calibration with known surface target, such as the Macbeth Color-Checker, improves our ability to estimate the illuminant SPD. This method may be useful in practical applications where a single calibration measurement is permitted.

Notation

We use matrix algebra notation to represent surface reflectance functions, illuminant spectral power distributions, and sensor responses. Surfaces are represented as functions of wavelength with N_w entries representing the spectral function. We represent the illuminant by an N_w vector, e, whose entries contain the spectral power distribution at the sample wavelengths. We represent the surface reflectance as a diagonal matrix, S, whose entries are the reflectance values at the N_w sample wavelengths. The sensor responsivities at the sample wavelengths are defined by the three columns of the $N_w \times 3$ matrix, X.

If we know the values of the $N_w \times 3$ matrix X, the $N_w \times N_w$ diagonal matrix, e, and the N_w, surface reflectance vector, S, then the calculation of sensor's responses to surfaces, S, illuminated by illuminant e is straightforward.

$$r = X^t S e \qquad (1)$$

where r is a three-dimensional vector containing the *XYZ* values. [1]

The calculations we describe in this paper use the standard CIE 1931 observer functions $\bar{x}, \bar{y}, \bar{z}$ (Wyszecki & Stiles, 1982).[2]

Linear Model Estimation Methods

Three sensor devices contain very little information about the spectral power distribution of the illuminant. From Equation 1, we see.that the sensor provides only the three entries in the vector, r. The unknown quantities on the right include both the surface reflectance function and the illuminant spectral power distribution. To make any headway, we need to make some guesses about both the sur- face and illuminant.

Surface Restrictions

Many investigators (Land, 1983; Buchsbaum, 1980; Evans, 1971) have assumed that the average reflectance function in the image is a constant spectral function, an 18 percent gray.[3] But these are usually used in appearance transforms, not calibration transforms.

By making the assumption that average spectral reflectance in the image is an 18 percent gray, the problem of recovering the illuminant from the sensor's response to the surface can be simplified immediately since the matrix S is known. By grouping X^tS together, we find that we have only a single unknown vector, the illuminant, e. This improves the situation, but we still have an underdeter-mined equation in which we have three measurements and $N_w >> 3$ unknowns.

Illuminant Restrictions

Buchsbaum (1980) and others solved this problem by assuming that the illuminant vector, e, can be approximated by a three-dimensional linear model. The linear model

contains a priori information about the distribution of likely illuminants and works smoothly with linear computations. To define a linear model we choose a set of basis functions, B_i, and we approximate any possible illuminant as the weighted sum of these basis functions,

$$e \approx \sum_{i=1}^{i=N} w_i B_i .$$

The weights, w_i, are chosen to minimize the squared error between the illuminant and its linear model approximation, and *N is* called the *dimension* of the linear model.

Call *B* the matrix whose columns are B_i; call the vector of weights describing an illuminant *w*. The assumption that the illuminant is drawn from a three dimensional linear model reduces Equation 1 to the form

$$r = X^t SBw. \qquad (2)$$

Under this restrictive set of assumptions, it is easy to estimate the illuminant. We can invert the known 3×3 matrix, X^tSB, and solve for the unknown weights, *w*. The illuminant estimate is *Bw*.

Once the illuminant is estimated, one can use linear models again to estimate the surface reflectance functions. Having estimated the surface reflectance functions, we can calculate the predicted *XYZ* values of the surfaces under other illuminants. These linear models have been used and analyzed by a large number of authors (Buchsbaum, 1980; Wandell, 1987; Maloney and Wandell, 1986; Funt and Drew, 1988; Ho et al, 1990; Marimont and Wandell, 1992; D'Zmura and Iverson, 1993a, 1993b)

There are two ways to improve the estimation process. First, knowing the true mean surface reflectance, or equivalently knowing the surface reflectance of a single object in the scene, improves the arbitrary assumption that the mean reflectance function is an 18 percent gray. Second, if we learn more about the set of possible illuminants we will be able to improve the linear model and hence our estimates.

Even so, this basic method is limited by the use of three-dimensional illuminant models. If the set of possible illuminants cannot be well-described by a three-dimensional linear model, sometimes we will obtain poor estimates. Although 3 spectral basis functions are sufficient to describe different types of daylight (Judd, MacAdam and Wyszecki, 1964) they do less well at describing the mixtures of daylight, tungsten and fluorescent illuminants commonly encountered in home and office environments.

Known Collection of Surfaces

To improve the illuminant estimation we would like to have more information. One method of obtaining more information is to use the light reflected from several surfaces, with known reflectance functions. The sensor responses to these surfaces should contain enough information so that we are no longer restricted to three-dimension-al linear models of the illuminant (Marimont and Wandell, 1992). The price we pay is the need to make an additional measurement of a calibration target.

We can represent the information available in the array of responses to the calibrated surfaces, S_i, as follows. Call the sensor responses to the the i^{th} surface is $r_i = X^tS_ie$. Group the receptor responses into a single long vector, r_N. Group the $3 \times N_w$, matrices X^t and S_i into a single N x N_w, matrix, X_N. The result is a single matrix equation,

$$r_N = X_N e \qquad (3)$$

in which the only unknown quantity is the illuminant.

From standard results in linear algebra, we can estimate that part of the illuminant within the subspace span-ned by the rows of the matrix X_N. By selecting a reasonable collection of surfaces, such as those in the Macbeth ColorChecker™, we obtain an estimate of the illuminant that is from a much larger space of possible illuminants than is possible with methods based on three-dimensional linear models.

Summary

We have simulated these illuminant estimation methods using of illuminants typical of windowed office environments. The simulations show how performance improves as we begin with the linear model methods, with no information about the specific scene, to methods in which we obtain a calibration measurement from the 24 surface reflectances in the Macbeth ColorChecker.

The White Point

We begin this talk distinguishing between *calibration* and *appearance* transforms because these two different types of transforms are frequently confused. This confusion is reinforced by current color representations that confound these two notions in a single parameter, the white point vector.

Perhaps the best known observation relating calibration and appearance transforms is that they are not the same. Consider a surface presented on a neutral background under one illuminant with tristimulus value *XYZ*. When we change the illuminant the surface tristimulus value will change, to say (*XYZ*)' If we ask an observer to find a tristimulus value of a surface on the newly illuminated background that matches the first, the setting will be (*XYZ*)" which will be different from (*XYZ*)'. A recent review of some aspects of appearance transforms is in Wandell (1993). The reader may also wish to consult recent articles by Hunt (1982a, 1982b), Hunt and Pointer (1985), Nayatani et al (1987, 1990), Fairchild and Berns, 1993), Poirson and Wandell (1993), Brainard and Wandell (1991, 1992) and Chichilnisky and Wandell (1993).

But, there is also a more subtle relationship between the two transforms which complicates their usage. When we perform a calibration transform, ordinarily we apply the transform to all of the surfaces in the image. But, when we speak of an appearance transform, we ordinarily perform a calibration transform of all the surfaces in the image but one, and then we set an appearance match for this one surface. It makes no sense to apply appearance transforms to all of the surfaces in the image; appearance transforms apply to a spatially localized region of the image to correct for the calibration transform elsewhere.

Part of the confusion is due to the widespread use of a single vector, the *white point,* to serve as a key parameter in

both appearance and calibration transforms. The white point refers to the *XYZ* values of a particular surface. It is used in colorimetric calculations that do not involve appearance. The white point is also used in appearance transforms. In these cases, it is used to approximate an object that appears white. Since the same surface does not generally look white in the two contexts, the use in appearance transforms is only an approximation.

But, worse than the approximation is the fact that the multiple uses of the white point in appearance and calibration representations leads to considerable confusion. Experts in color are familiar with this multiple usage; to them it serves as a minor nuisance. But, engineers and scientists who learn about color science and engineering correctly perceive these uses of the white point as a muddle that is difficult to clarify. Perhaps some discussion on this topic is in order.

References

1. The formulae we introduce here only apply to materials without fluorescence.
2. In this paper, calibration transforms map *XYZ* values of a surface surface measured under one illuminant into an estimate of the *XYZ* values we expect when the surface is measured under a different illuminant. One might imagine defining calibration transforms to map other sensor responses across different illuminants, such as the responses of video cameras, flatbed scanners and digital cameras.
3. Although this assumption is not generally true, Evans (1971) described how Kodak used it to color balance photographs.
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