Controlling Illumination Color to Enhance Object Discriminability

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Abstract

We describe how to design color illumination to improve the discriminability of objects in color images. This procedure is useful in applications where the illumination can be controlled such as inspection tasks. From the physics of color image formation, we derive the optimal color illumination for discriminating materials using a parametrically defined set of illuminants. We suggest how such an approach might be extended to sets of materials and more general classes of light sources. We use experiments with painted color patches and live potato plantlets to demonstrate the approach. These experiments illustrate the usefulness of actively controlling illumination color in machine vision.

1 Introduction

How an object appears to a machine vision system is profoundly affected by the illumination, the image sensors, and the scene geometry. It stands to reason that by carefully choosing illuminants and sensors and by configuring them appropriately with respect to the objects in a scene, we can simplify many visual tasks. This is particularly important for automatic visual inspection [1] where many aspects of the imaging system and configuration can be actively controlled. Being able to optimize imaging system design is important for several reasons. Image processing hardware and software are expensive and many months of development time might be required to develop an image processing module for a machine vision system. An effective image acquisition system will significantly reduce the complexity of the image processing module. Perhaps more serious is the possibility that an image acquisition system might generate images which are inadequate for an inspection task. Relevant defects might, for example, be buried in noise or unresolvable in the captured images. In these situations, even the best image processing algorithms will not be able to recover the signal of interest from the acquired image.

In this paper, we show how color illumination can be designed to improve the discriminability of objects in color images. Improved discriminability often leads to higher system speed and lower cost as well as improved accuracy of algorithms. We have applied our approach to images of painted surfaces and live potato plantlets.

2 The Camera Model

We partition the visible wavelengths into nonoverlapping red [λ_R0, λ_R1], green [λ_G0, λ_G1], and blue [λ_B0, λ_B1] color bands that correspond to the regions of sensitivity of a color camera. At each pixel, a color camera produces a triplet (R, G, B) with

\[ R = \int_{\lambda_B}^{\lambda_R} i(\lambda) s(\lambda) f_R(\lambda) d\lambda \]
\[ G = \int_{\lambda_G}^{\lambda_G} i(\lambda) s(\lambda) f_G(\lambda) d\lambda \]
\[ B = \int_{\lambda_B}^{\lambda_B} i(\lambda) s(\lambda) f_B(\lambda) d\lambda \]

where i(\lambda) is the illumination power spectrum, s(\lambda) is the spectral reflectance of the object in the direction of the camera, and f_R(\lambda), f_G(\lambda), and f_B(\lambda) are the camera spectral response functions for the red, green, and blue color bands.

3 Optimal Color Illumination

In this section we describe how to design a color illumination that maximizes the discriminability of materials. We begin by assuming that the scene illumination consists of impulse functions \( i_R(\lambda - \lambda_R) \),
$iR(\lambda - \lambda_R)$, and $iB(\lambda - \lambda_B)$ centered at wavelengths $\lambda_R \in [\lambda_0, \lambda_1]$, $\lambda_G \in [\lambda_0, \lambda_1]$, and $\lambda_B \in [\lambda_0, \lambda_1]$. When two objects with spectral reflectance functions $s_1(\lambda)$ and $s_2(\lambda)$ are illuminated with such a source the measured sensor values are

$$R_1 = iR f_R(\lambda_R)s_1(\lambda_R), \quad R_2 = iR f_R(\lambda_R)s_2(\lambda_R)$$

$$G_1 = iG f_G(\lambda_G)s_1(\lambda_G), \quad G_2 = iG f_G(\lambda_G)s_2(\lambda_G)$$

$$B_1 = iB f_B(\lambda_B)s_1(\lambda_B), \quad B_2 = iB f_B(\lambda_B)s_2(\lambda_B)$$

We define a color contrast vector by $\Delta = (\Delta_R(i_R, \lambda_R), \Delta_G(i_G, \lambda_G), \Delta_B(i_B, \lambda_B))$ where

$$\Delta_R(i_R, \lambda_R) = |R_1 - R_2| = iR f_R(\lambda_R)s_1(\lambda_R) - s_2(\lambda_R)$$

$$\Delta_G(i_G, \lambda_G) = |G_1 - G_2| = iG f_G(\lambda_G)s_1(\lambda_G) - s_2(\lambda_G)$$

$$\Delta_B(i_B, \lambda_B) = |B_1 - B_2| = iB f_B(\lambda_B)s_1(\lambda_B) - s_2(\lambda_B)$$

The norm of the color contrast vector $||\Delta||$ is a measure of the discriminability of two objects as a function of the scene illumination. Given our illumination model, maximizing $||\Delta||$ can be performed by maximizing separately $\Delta_R$, $\Delta_G$, and $\Delta_B$. Therefore, we will determine how to choose $i_R$ and $\lambda_R$ to maximize $\Delta_R$ given the spectral sensitivity $f_R(\lambda)$ and the spectral reflectance functions $s_1(\lambda)$ and $s_2(\lambda)$. Values for $i_G$, $\lambda_G$, $i_B$, and $\lambda_B$ that maximize $\Delta_G$ and $\Delta_B$ may be computed in a similar way. Let $R_{max}$ denote the largest $R$ value that can be represented by our imaging system. Thus, for fixed $\lambda_R$, we maximize $\Delta_R$ by choosing $i_R$ according to

$$i_R(\lambda_R) = \frac{R_{max}}{f_R(\lambda_R)\text{max}\{s_1(\lambda_R), s_2(\lambda_R)\}}$$

From (7), the corresponding value of $\Delta_R(i_R, \lambda_R)$ is

$$\Delta_R(i_R, \lambda_R) = \frac{R_{max}|s_1(\lambda_R) - s_2(\lambda_R)|}{\text{max}\{s_1(\lambda_R), s_2(\lambda_R)\} \cdot \text{max}\{s_1(\lambda_R), s_2(\lambda_R)\}}$$

Using (11), $\Delta_R(i_R, \lambda_R)$ can be maximized for $\lambda_R \in [\lambda_0, \lambda_1]$ using standard techniques. Once $\lambda_R$ is determined, the corresponding $i_R$ is computed using (10).

While the analysis of this section applies only to the class of light sources that can be characterized using our parametric power spectral model, the concept may be readily extended to any set of sources. The key idea is that, in general, object discriminability depends on the spectral power distribution of the illumination. For a given application, therefore, a search over available illuminants will yield an illuminant that maximizes discriminability. In the next section, we discuss experiments that demonstrate this concept.

4 Experimental Results

In this section, we present the results of two experiments in which we determined empirically the optimal illumination for discriminating the following objects: (1) painted color patches and (2) leaves and stems of live plantlets. In these experiments, we measured and compared the discriminability of the objects under each of 16 color illumination conditions created by using a set of white lights in conjunction with various combinations of color filters. The discriminability was estimated using the Mahalanobis metric [2] that is a generalization of the color contrast vector norm defined in section 3. The spectral response curves for our color camera are shown in figure 1.

4.1 Results from Standard Color Patches

In the first experiment, we considered the problem of discriminating color patches on the Macbeth color chart [3]. We assumed that color illumination was to be chosen from a set of sixteen illumination conditions available using our experimental setup. The Mahalanobis distance between each pair of color patches was computed for each illumination condition. The results indicate that the discriminability of these surfaces depends strongly on properties of the illumination. In figure 2, for example, we plot the discriminability of red and green color patches for each of the sixteen color illumination conditions. This figure shows that BB is the least effective illumination for discriminating
these surfaces and GR is the most effective. If our goal is to choose illumination to maximize discriminability over a set of several surfaces, then we find the illumination condition that maximizes the contrast between the two least discriminable surfaces under that illumination.

4.2 Results from Live Potato Plantlets

In our second experiment, we selected a color illumination condition to enhance the contrast between the leaves and stem of a live potato plantlet. The same sixteen color illumination conditions used for the previous experiment were considered. Figure 3 shows the Mahalanobis discriminability for leaves and stem over the available lighting conditions. From this figure, we see that the illumination condition WB produces the best discriminability. Note that most of the other illumination conditions produce a Mahalanobis discriminability that is only about half of the maximum discriminability.

5 Conclusion

We have shown that illumination color can be controlled to improve the discriminability of materials in color images. Our analysis has been supported by experiments using various kinds of materials and illumination conditions. The concepts presented in this paper can be used by image acquisition system designers to improve the effectiveness of the illumination component of a color imaging system.

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References