The Use of Color in Highlight Identification

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Abstract

This paper presents a method for identifying highlights in images through the use of chromatic information. An existing model of reflectance is shown to predict that a highlight will usually involve a gradual additive color shift from the color of the object to the color of the illuminant. This shift is observed in real images and forms the basis of our algorithm.

1 Introduction

The appearance of objects in the real world is related to the complex ways they reflect the light impinging on them from the light source present. Different materials reflect light in various ways, but one thing common to most materials is the fact that they are neither totally matte nor totally mirror-like; it is a combination of these two modes of reflection that governs the appearance of most objects. In short, it is the sum of diffuse and specular reflections that determines the total reflection of light off surfaces. Based on this statement, we observe that a shift in color occurs under some conditions, which leads to the development of an algorithm designed to identify the color changes which are due to specular reflection.

The motivation behind the quest for highlights originates in two opposing properties highlights possess. On one hand, highlights in images provide important information which can be used to determine shape, size, or curvature of objects [1,2,3,9]. On the other hand, highlights cause numerous problems for algorithms which require correspondence between consecutive images, such as stereo or motion algorithms [6,8].

2 The Shift in Color

Earlier studies into models of reflection pointed out that the total reflection of light striking an object is actually a sum of two components: specular and diffuse [4,7]. This combination determines the appearance of the object everywhere, be it shadow, highlight, or any other region. The most intriguing aspect of this statement is the fact that specularity is an additive process; that is, the regions which appear glossy have the color of the illuminant added to the diffuse color of the surface for nonxnetallic objects. The reason for this transition is a change in the weights (magnitudes) assigned to the diffuse and specular reflections. A realistic formulation of the physical processes which vary these weights is found in [4]. One interesting observation from this formulation is that as the viewing and illumination geometry changes, there is a shift in the relative strengths of the diffuse and specular reflections, from a stronger diffuse reflection to a stronger specular reflection. Since this is in effect at all wavelengths, the implication on chromaticity will be a shift in color from the diffuse color to the color of the light source.

Suppose that the images with which we deal are transformed into a color constant space (*C-space),* one which is a linear transformation of the original [R,G,B] image into an image which discounts the illuminant; such a transformation is described in more detail elsewhere [5]. We therefore assume that the image has been transformed in such a way that no matter what illuminant is used in the scene, the C-values[1] of each pixel in the image will be the same. This implies that if the highlights indeed reflect the color of the light source, then changing the light source for the same scene should result in the same C- values for the highlight regions. Thus the shift in color from the diffuse regions to the highlight regions should involve a transition from some C-values representing the (diffuse) color of the object to C-values representing the perfect reflector (mirror). Moreover, barring any abrupt changes in the curvature or pigmentation of the object, the transition should be smooth, reflecting the monotonic change between the diffuse and specular reflections. This transition is the phenomenon we wish to use as a cue towards the detection of highlights.

In order to verify that indeed the shift in color occurs in real images, some instances of highlights in images were sampled and plotted in C-space. The images were transformed into C-space and scatter plots of the C-values were generated. The regions from which the C-values were picked were always a highlight and a diffuse region beside it. One example is presented in Figure 1, where a three-dimensional scatter plot of the C-space from the "cup" image is depicted, illustrating that around a highlight area there is a "dog leg" structure of the among the pixels. The original image is presented in Plate I.[3] As can.be observed in the figure, there is indeed a smooth transition in the C-values in the form of a "dog leg". Moreover, the transition always involves

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[1]The [R,G,B] values transformed into C-space.

[3]This image was provided by Professor Steve Shafer of the Calibrated Imaging Laboratory at Carnegie Mellon University, supported by the National Science Foundation and the Defense Advanced Research Projects Agency.

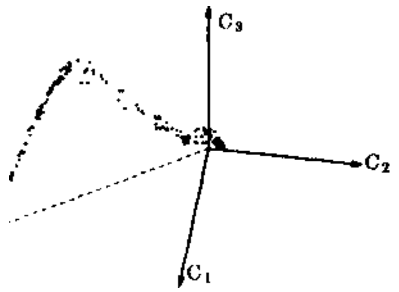

Figure 1: Scatter plot of highlight and surrounding cup. The dashed line represents reflectances of perfect reflectors.

a shift of the C-values towards the same direction. In terms of the C-space, this direction is actually pointing towards the values of a perfect reflector, since highlights are supposedly a realization of mirror-like surfaces. This observation was analyzed numerically in the following way. C-values of a perfect reflector were generated under the assumption that a perfect reflector would reflect the light impinging on it at all wavelengths. The resulting C-values for a perfect reflector in wavelengths $\lambda \in [400, 650]$ were: $C_1 = 1.340$, $C_2 = -0.176$, and $C_3 = -0.009$. This claim is illustrated in Figure 1 with a (dashed) line segment starting at the origin and ending at the C-values of a perfect reflector, as given above. This line segment represents the C-values which reflect light equally at all wavelengths, for reflectances from 0 to 100%. We can see that one of the legs points towards the end of this line segment.

3 The Algorithm

The algorithm designed to detect possible highlights is based on the observations made in the previous section. It is a two step algorithm: first, it requires the segmentation of the image into regions, and compilation of information about regions and neighbors, and secondly, it attempts to find a "dog leg" relationship between every adjacent pair of regions. The major steps of the algorithm are:

- Chromatic-based segmentation of the [R,G,B] image and aggregation of small regions into larger ones.
- Transformation of the [R,G,B] values into C-values.
- Least squares approximation of the C-values in each region to a line in 3-d.

For each pair of adjacent regions:

- Verification whether the lines ("legs") are parallel — if so, a new pair of regions is tested.
- Computation of the point of intersection between the two lines and verification that the two lines indeed meet.
- Detection of the region in which most of the C_1 values are beyond the point of intersection, and labeling it as a candidate highlight. If both regions pass the test — a new pair of regions is tested.
- Verification whether the line representing the candidate region is in the direction of a perfect reflector.

The algorithm was applied on the images presented in Plates 1 and 2, with the results of the regions considered as highlights depicted in Plates 3 and 4. In all the images, the highlight regions are coded in a grid pattern superimposed on the original image. Note that the shape of the regions does not precisely fit the shape of the highlights, due to the nature of the segmentation.

4 Discussion

One assumption which was not dealt with was the number of light sources and their spectral power distribution. Since the algorithm makes use of color constant descriptors of the image, and thus discounts *one* spectral power distribution of illuminants, the same assumption regarding the light source holds. Therefore the algorithm can handle more than one light source in the scene, as long as *all* the light sources share the same spectral power distribution. The fact that there are no assumptions regarding the geometry of the objects allows the treatment of many light sources, since the algorithm is based on chromatic properties only. The scatter plot resulting from the inclusion of more light sources will not change since there will be no change in the chromaticity of the light sources, and consequently, in the colors of the diffuse and specular regions.

There remains one problem with the technique employed in this paper, namely, highlights on materials which share the same color as the light source. A simple example can be a highlight caused by a white illuminant on a white object. The problem, of course, is that there will be no color shift, since the diffuse and specular reflections share the same spectral power distribution. This results in the fact that there will be no "dog leg" in C-space since the only difference between the two regions will be the strength of the values of C_1. This problem remains open at this stage.

5 Summary

This paper discussed the problem of identifying probable highlights in real images. The solution we have proposed is based on the physics of interaction between light and materials, as formulated in models of optics and reflection. Based on these models, a prediction as to the behavior of highlights, or the specular reflection, was made, and was observed in real images. Based on the observed phenomenon, namely, the shift in the color of objects from the diffuse reflection to the the specular one, we have developed an algorithm designed to detect these shifts. The algorithm requires a segmentation of the image into regions, so that each region can be related to its neighbors to verify whether they share the shift in color. Since the color shifts can be characterized by a "dog leg" behavior in color space, the algorithm was designed to detect such relationships between the regions, and augmented with rules that employ information about the expected color of highlights in the scene. The algorithm was tested with real images and produced good results in detecting the location of probable highlights.

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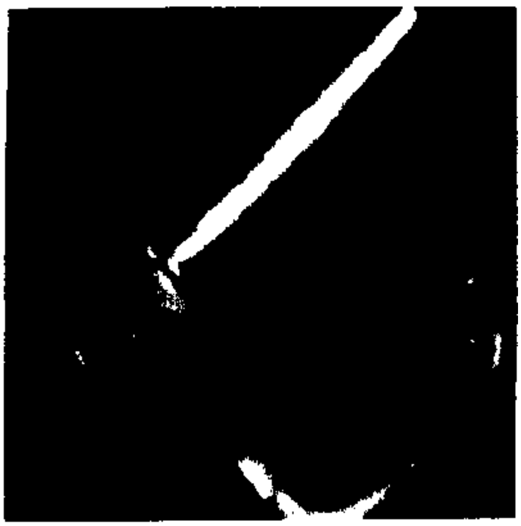

Plate 1

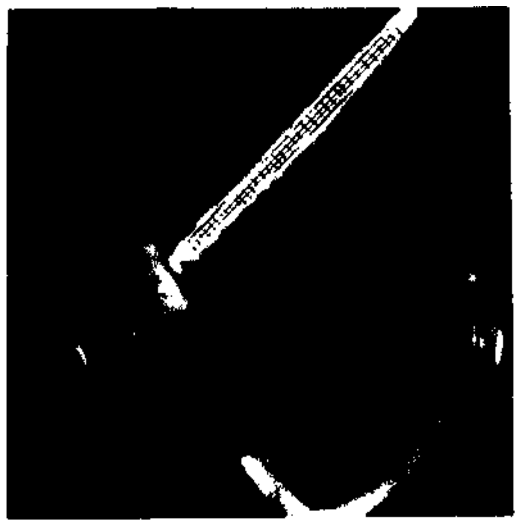

Plate 3

Plate 2

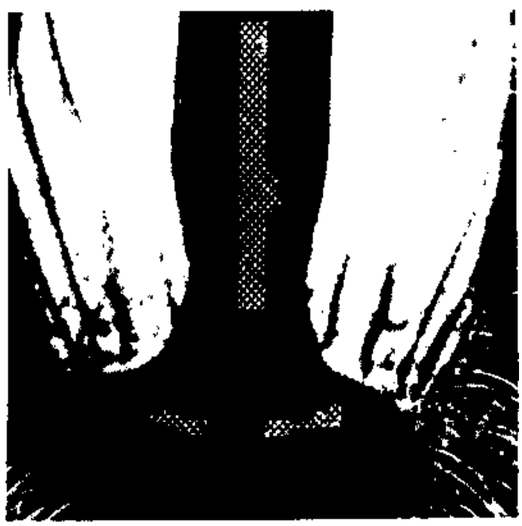

Plate 4