A Survey of Color Spaces for Shadow Identification

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Abstract

We have surveyed the quality of different color spaces for the purpose of shadow edge detection. Knowing which edges in an image denote shadow edges and which are due to object boundaries or changes in surface reflectance has important applications in computer vision, mixed reality, and image relighting.

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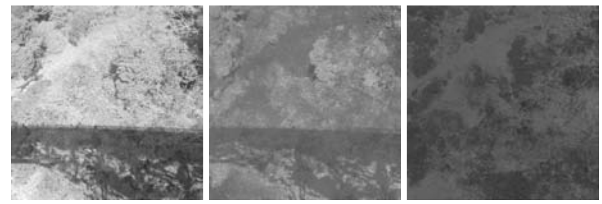

Figure 1: Shadow edges appear in the Luminance channel (left) and the Blue-Yellow chromatic channel (center), but not in the Red-Green channel (right) in $CIELAB$ color opponent space.

1 Introduction

Although color is an important feature for the task of shadow edge detection, so far the choice of color space has been given insufficient consideration. We have found that the color opponent spaces are a better choice than the color spaces routinely used for the detection of shadows, such as RGB, HSV and normalized rgb. These color opponent spaces feature decorrelated axes including red-green and blue-yellow chromatic axes, and are based on knowledge of human visual perception [Palmer 1999]. Recent discoveries in primate vision in the context of natural scenes have given extra arguments in favor of color opponent spaces, namely that the red-green channel is invariant to shadows (Figure 1). This is an important observation because it enables us to detect and remove shadows in outdoors scenes where there is a change in both luminance as well as chromaticity across shadow edges. As such, our understanding from both natural image statistics as well as primate vision allows us to extend the class of images for which we can successfully identify shadows to include outdoors scenes.

2 Pilot Study

Appropriate color spaces will show shadow edges in one or two channels, but should also have one channel in which shadows are consistently absent. The selection of color spaces we compare include device-dependent RGB, normalized rgb, XYZ, Yxy, LMS, $CIELAB$, $CIELUV$, $L\alpha\beta$ and HSV [Wyszecki and Stiles 1982; Ruderman et al. 1998]. Some color spaces show shadows in all three channels, while others have one or more channels that are insensitive to shadows. We have informally inspected a set of 23 scenes containing shadows in various natural settings, allowing for several important observations. First, we note that shadows are apparent in all three channels of RGB, XYZ and LMS color spaces. This is according to expectation and confirms that using color as a cue for shadow identification provides minimal advantages over grey scale images if these color spaces are employed.

The normalized rgb and Yxy color spaces did not show consistently good results. For most images one or two channels were able to subdue the presence of shadows, but it proved impossible to predict which channels would not respond to shadows. As expected, the Y channel in Yxy consistently shows both shadow and reflectance edges. This is also the case for all other color spaces which feature a luminance channel. The ability to remove shadows using $CIELUV$ is similar to HSV, where both the hue and saturation channels show promise for some images.

The two color opponent spaces we evaluate are $CIELAB$ and $L\alpha\beta$ space. Since both color spaces feature a luminance channel as well as red-green and yellow-blue opponent channels, we expect similar results. However, we find that the perceptually uniform $CIELAB$ color space shows the most consistent results across our set of test images. For most images shadows are reasonably well suppressed in the red-green channel, but show up in the luminance and yellow-blue channels.

3 Conclusion

Our pilot study shows that both color opponent spaces perform significantly better than any of the seven other color spaces we included and we therefore recommend their use for shadow edge detection. However, a more rigorous experiment will be necessary to verify our results.

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