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Specular Highlight Removal For Image-Based Dietary Assessment

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***Abstract*—Traditional dietary assessment methods, consisting of written and orally reported methods, are not widely acceptable or feasible for everyday monitoring. The development of built-in cameras for mobile devices provides a new way of collecting dietary information by acquiring images of foods and beverages. The ability of image analysis techniques to automatically segment and identify food items from food images becomes imperative. Food images, usually consisting of plates, bowls and glasses, are often affected by lighting and specular highlights which present difficulties for image analysis. In this paper, we propose a novel single-image specular highlight removal method to detect and remove specular highlights in food images. We use independent components analysis (ICA) to separate the specular and diffuse components from the original image using only one image. This paper describes the details of the proposed model and also presents experimental results on food images to demonstrate the effectiveness of our approach.**

***Index Terms*—Dietary assessment, diet record method, image analysis, specular highlight removal, independent components analysis, specular reflection.**

I. Introduction

Dietary assessment, the process of determining what someone eats during the course of a day, provides valuable insight for mounting intervention programs for the prevention of many chronic diseases including obesity, cancer, diabetes, and heart disease [1], [2]. Traditional dietary assessment, consisting of written and orally reported methods are time consuming and tedious and often require a nutrition professional to complete, is not widely acceptable or feasible for everyday monitoring [3]. Mobile devices with high resolution imaging capability, improved memory capacity and network connectivity provide a unique mechanism for collecting dietary information and thus reducing burden on both users and healthcare professionals. The importance of using food images to record and estimate dietary intake, in comparison to classical handwritten food record approaches have described [4]. Our team at Purdue University and the University of Hawaii is developing a mobile telephone based image analysis system to automatically estimate energy and nutrient intake from food images acquired by mobile devices [5], [6]. In order to minimize user-burden in using image-based dietary assessment, it is important to use as few images as possible and preferably design single-image based image analysis techniques. An essential part of our system is food image segmentation. However, food images, consisting of plates, bowls and glasses, are often affected by lighting and specular highlights, which present difficulties for image segmentation. Figure 1 shows examples of food images affected by specular highlights.

Fig. 1. Examples of food images with specular highlights.

Many methods developed for separating specular and diffuse reflection components require multiple images taken under specific conditions (e.g., lighting direction and viewpoint). A sequence of color images captured with a moving light source is examined in [7] in a four-dimensional space, the axes of which are the three color compenets (RGB) and time. While this method requires dense input images, it can separate specular and diffuse reflection components locally using principal component analysis based solely on colors. Nayar et al. [8] used color and polarization information from multiple images captured with various polarization angles to estimate the color of specular reflection. Lee et al. [9] detected specular reflection by color differences between input images from different viewing directions without using feature correspondence or image segmentation. Lin et al. [10] proposed a diffuse and specular reflection separation method based on the neutral interface reflection model [11] which describes which specular reflection has the same spectral composition as the incident illumination. Two input images are required to estimate the illuminant chromaticity and compute the RGB intensities of the two reflection components using a linear model of surface reflectance. Farid and Adelson [12] proposed a reflection separation method using independent component analysis. Two images with specified reflection directions are required to obtain stable reflection separation results.

For dietary assessment, acquiring multiple food images of

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each eating occasion would place heavy burden on users, thus we need to explore specular reflection removal methods using a single input image. One of the early methods to separate the two components of reflection using one image is presented by Shafer [13], who introduced the dichromatic reflection model and discussed the geometric properties of each type of reflection. Klinker et al. [14] then extended this model by separating reflection and illumination color vectors based on a T-shaped color distribution. The model presented in [15] separated specular and diffuse reflections in brightness, hue and saturation color space. The above models using a single input image requires color segmentation which limits the robustness of those models.

In this paper we propose a specular highlight removal method that does not depend on either polarization or image segmentation. Based on observation of color properties in the highlight area and a linear combination model, we show that with a single input image, specular highlight can be effectively removed using independent component analysis (ICA). We then use color compensation on this "highlight-free" image to ensure local smoothness of color and luminance. Our method is somewhat similar to the Farid and Adelson's model [12] with repesct to using independent component analysis (ICA) to separate reflection components. However instead of requiring two images our method needs only one image. Further, the input image to our specular highlight removal method need not be acquired with any specific conditions (e.g. illumination, lighting direction, and viewpoint). Our proposed method can be used with any images with specular highlighted areas. Since the goal of our study is to improve image segmentation for food images acquired in our dietary assessment studies, this paper presents only the results on food images.

II. Proposed Method

In this section we first briefly review the dichromatic reflection model and then describe the details of our method. Figure 2 shows the block diagram of our proposed method. The first step is to generate an "assisting gray image" based on the color properties of the specular highlighted areas. The second step is to use this assisting gray image and the original image as two inputs to ICA to remove specular highlights from the original image. The result is a "highlight-free" image. Finally, color compensation is done on the highlight-free image to maintain local color smoothness.

The dichromatic reflection model [13] describes how reflected light can be separated into two components, specular and diffuse reflection. The combination of specular and diffuse reflection components can often be approximated as a linear mixing process. Thus, the illumination spectral distribution of a point can be expressed as:

$$I(\lambda, p) = \omega_d I_d(\lambda, p) + \omega_s I_s(\lambda, p) \tag{1}$$

where p is a 3 dimensional vector which represents the position (3D coordinates) of a point; ω_d and ω_s are the coefficients (at position p) of the diffuse and specular reflection respectively. $I_d(\lambda, p)$ and $I_s(\lambda, p)$ are the illumination spectral distribution contributed by the diffuse and specular reflection, respectively. Hence, the illuminance value of an image can be obtained by integrating Equation 1 over the visible spectrum (Ω):

$$\begin{aligned} I_c(x) = \omega_d \int_\Omega I_d(\lambda, x) \mathrm{d}\lambda \\ + \omega_s \int_\Omega I_s(\lambda, x) \mathrm{d}\lambda \end{aligned} \tag{2}$$

where x is two dimensional coordinate of an image and $I_c(x)$ ($c \in \{r, g, b\}$) is the R, G, B value of the image at position x.

Based on Equation 2, the original image is a linear mixing process of the specular reflection component and the diffuse reflection component. But the parameters ω_d and ω_s in Equation 2 are unknown, and $I_d(\lambda, x)$ and $I_s(\lambda, x)$, which depend on the light sources and properties of the objects and cameras, are also not easy to measure. The problem of separating diffuse and specular reflection requires isolating signals from mixtures of signals, for which both the source signals (diffuse and specular reflection) and mixing coefficients are unknown. This is a typical scenario that can be addressed using Independent Component Analysis (ICA) [16], [17], [18]. Since ICA requires the number of measurements to be greater than or equal to the number of independent components, we need to generate an image to assist the reflection separation process of ICA.

By experimentation, we observed that the value of the luminance component in the specular highlighted area is usually larger than that in neighboring areas, while the value of maximum chromaticity in the specular highlighted area is smaller than that in neighboring areas with the same color. This observation is reasonable because the luminance of a 'highlight' area is larger than the surrounding areas and the increase of the luminance component may cause the decrease of the chrominance fraction. An "assisting gray image" is generated automatically based on this observation.

We obtain the luminance fraction in YCbCr color space as follows:

$$\Gamma = \frac{m_Y}{\Sigma_{i \in (Y, Cb, Cr)} m_i} \tag{3}$$

where $i \in \{Y, Cb, Cr\}$ and m_i is the value of the ith component of the original image in YCbCr color space. The maximum chromaticity is defined as the fraction of the maximum chroma component in RGB color space:

$$\Lambda = \frac{max(m_r, m_g, m_b)}{\Sigma_{j \in (r,g,b)} m_j} \tag{4}$$

where $j \in \{r, g, b\}$ and m_j is the value of the jth component of the original image in RGB color space. It is easy to conclude from Equations 3 and 4 that $\Gamma \in [0, 1]$ and $\Lambda \in [1/3, 1]$.

The assisting gray image is then generated using Equation 5.

$$I(x, y) = (\Gamma(x, y) - \Lambda(x, y)) \times 255 \tag{5}$$

where $I(x, y)$ is the luminance value of the gray image at position (x, y); $\Gamma(x, y)$ and $\Lambda(x, y)$ are the luminance fraction and the maximum chroma fraction respectively. From this equation, we could see that the specular highlight areas are

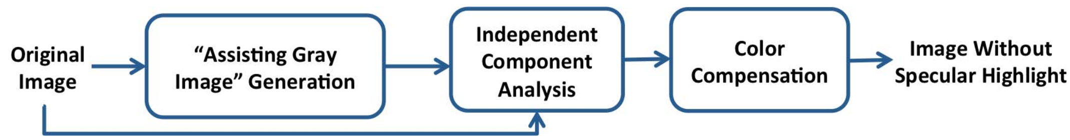


Fig. 2. Block diagram of our proposed method for specular highlight removal.

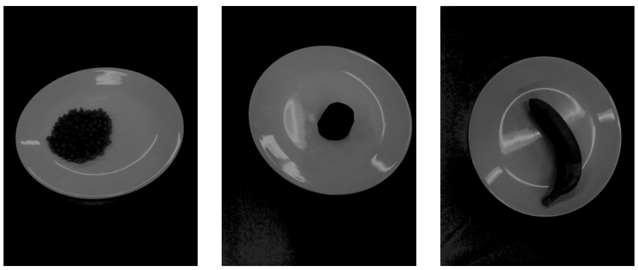


Fig. 3. Examples of the assisting gray images.

emphasized in the assisting gray image. Examples of the generated assisting gray images corresponding to the original images in Figure 1 are shown in Figure 3.

After generating the assisting gray image, we now have two input components (the assisting gray image and the original image) for ICA to separate the specular reflection component from the original image. ICA achieves this by tuning the mixing coefficients to maximize the mutual independence of the estimated signals. Denote the original image and the assisting gray image in N dimensional row vector form as I_{org} and I_{gray}, respectively. Then the linear mixing can be expressed as follows:

$$\begin{bmatrix} I_1 \\ I_2 \end{bmatrix} = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} I_{org} \\ I_{gray} \end{bmatrix} \quad (6)$$

where I_1 and I_2 are the separated output images. The parameter matrix is assumed to be a full rank coefficient matrix which can be estimated using Farid and Adelson's model [12]. I_2 contains mainly the specular highlight component. Therefore we can detect specular highlight areas using I_2 and refine our separation result by a color compensation process on the specular highlight areas.

The color compensation is obtained by considering the chromaticity of k nearest neighboring pixels without specular highlight. In our implementation, we set $k = 8$. The nearest pixels are checked in the direction shown in Figure 4 until k pixels without specular reflection have found. The color of the current pixel equals to the average color of the k neighbors without specular highlight.

III. Experimental Results

In the experiments presented here, our specular highlight removal method is tested on a collection of food images acquired by mobile telephone cameras. We investigated food images acquired in a controlled environment and in natural eating conditions (also referred to as "free-living" such as at home, restaurants and on the go). Figure 5 shows the results

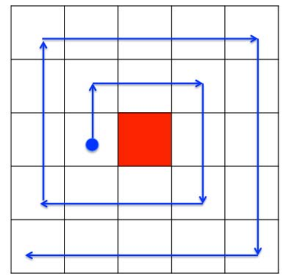
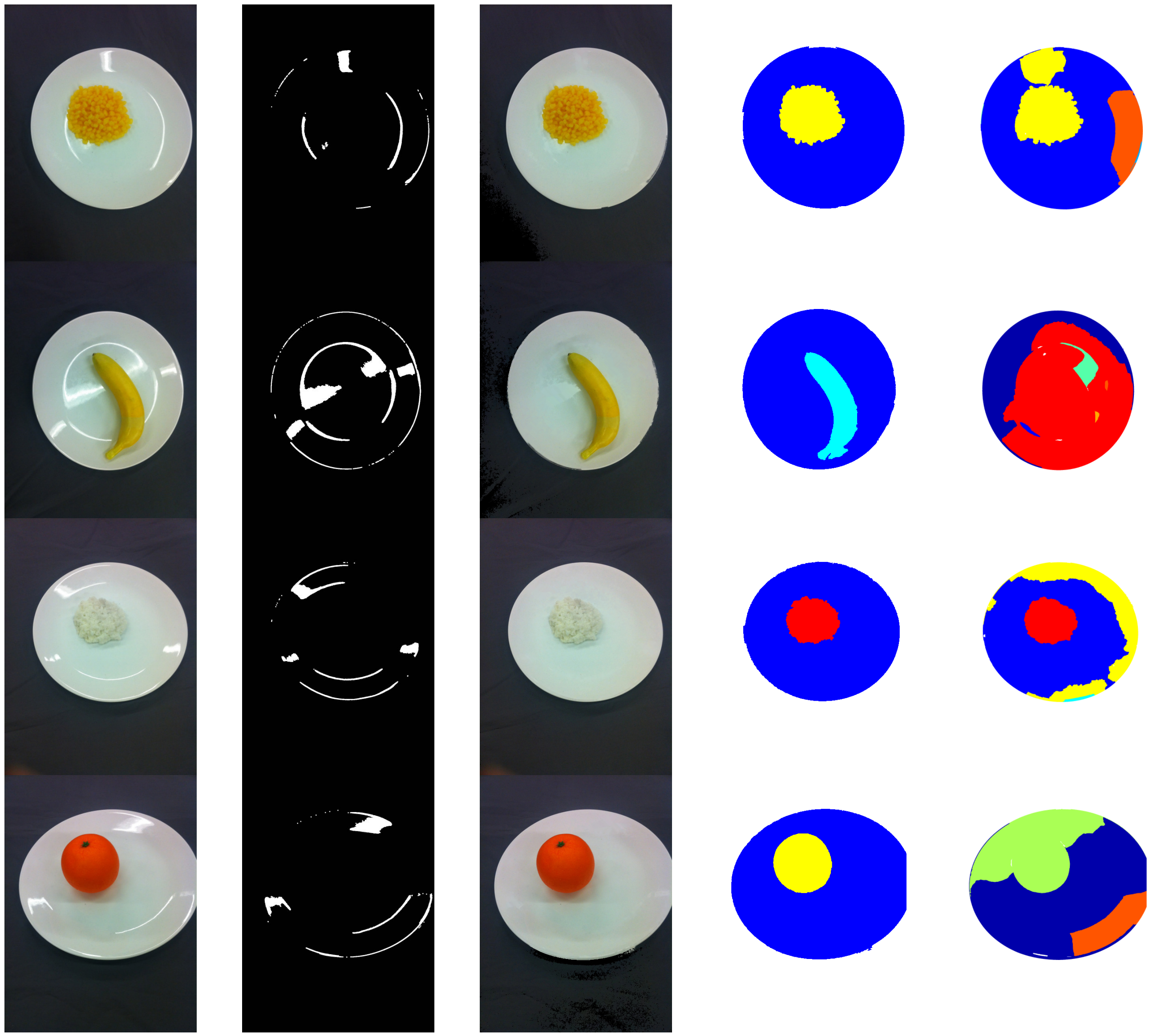


Fig. 4. Direction of searching nearest neighboring pixels for color compensation (The red block indicates current pixel and the blue dot represents the starting pixel).

on food images acquired under controlled lab settings. When taking food images in our lab, we move the cameras randomly in order to generate specular reflection at random positions. Figure 6 shows the results for food images acquired during free-living studies. In both Figure 5 and 6, the original food images are shown in column (a). The mask or region of the specular highlight area detected by our method is shown in (b). The image of mask is a binary image in which black pixels indicate areas without specular highlights while the white pixels indicate the specular highlight area detected by our method. The images in column (d) and (e) show the result of image segmentation with respect to the corresponding images in column (c) and (a) respectively.

In our experiments we use the segmentation method based on the Normalized Cuts framework. Normalized Cuts is a graph partition method first proposed in [19], which treats an image pixel as a node of a graph and formulates segmentation as a graph partitioning problem. In order to compare the segmentation results of highlight-free images and original images, we used the same segmentation method on the highlight-free images obtained by our method and the corresponding original image. The comparison between segmentation results of highlight-free images and that of original images in Figures 5 and 6 illustrates improvement in the image segmentation.

In addition, Figure 7 shows that our method is robust to images without obvious specular highlighted areas. Figure 7 (a) is an image without specular highlights. We used our method on the original image to generate the binary mask image (Figure 7 (b)) and the output highlight-free image (Figure 7 (c)). The mask image is black in the entire plate area indicates that no specular reflection is detected. We can also see from Figure 7 (c) that our method does not produce artifacts in images without specular highlights.



(a) Original Images (b) Highlight Mask (c) Highlight-Free Images (d) Segmentation of (c) (e) Segmentation of (a)

Fig. 5. Experimental results of our proposed method using food images acquired in controlled experiments; (a) original input image; (b) mask of detected specular highlight area; (c) generated highlight-free image; (d) segmentation results for highlight-free images; (e) segmentation results for original input images.

IV. Conclusions

The accuracy of food image segmentation is essential to mobile dietary assessment. In this paper, we proposed a specular highlight removal method using a single color image to improve the segmentation results of food images. Our experimental results on food images show the effectiveness of our method in specular highlight detection and removal and also show the improvement of segmentation results after specular highlight removal.

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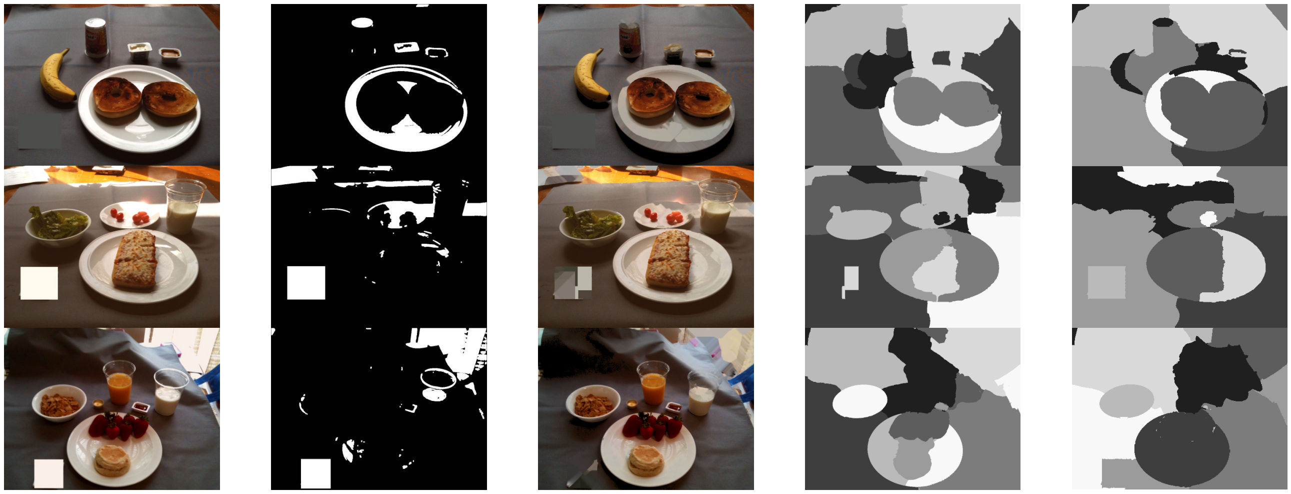
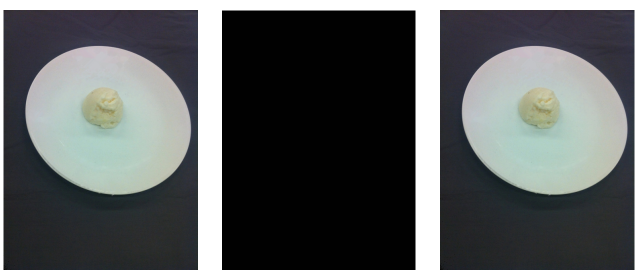
References

[1] C. L. Ogden, M. D. Carroll, L. R. Curtin, M. M. Lamb, and K. M. Flegal, "Prevalence of high body mass index in US children and adolescents, 2007-2008," *Journal of the American Medical Association*, vol. 303, no. 3, pp. 242–249, January 2010.



(a) Original Images (b) Highlight Mask (c) Highlight-Free Images (d) Segmentation of (c) (e) Segmentation of (a)

Fig. 6. Experimental results of our proposed method on food images in free-living studies; (a) original input image; (b) mask of detected specular highlight area; (c) highlight-free image; (d) segmentation results for highlight-free images; (e) segmentation results for original input images.



(a) Original Image (b) Highlight Mask (c) Output Image

Fig. 7. Illustration of specular highlight removal on highlight-free images; (a) original input image (b) a binary image indicating the mask of specular highlight area (c) result of using our method on the original image.

[2] A. Fagot-Campagna, J.B. Saadinem, K.M. Flegal, and G.L.A. Beckles, "Diabetes, impaired fasting glucose, and elevated hba1c in US adolescents: the third national health and nutrition examination survey," *Diabetes Care*, vol. 24, no. 5, pp. 834–837, May 2001.

[3] F. E. Thompson, A. F. Subar, C. M. Loria, J. L. Reedy, and T. Baranowski, "Need for technological innovation in dietary assessment," *Journal of the American Dietetic Association*, vol. 110, pp. 48–51, Jan 2010.

[4] B. L. Six, T. E. Schap, F. Zhu, A. Mariappan, M. Bosch, E. J. Delp, D. S. Ebert, D. A. Kerr, and C. J. Boushey, "Evidence-based development of a mobile telephone food record," *Journal of the American Dietetic Association*, vol. 110, pp. 74–79, Jan 2010.

[5] F. Zhu, M. Bosch, C.J. Boushey, and E.J. Delp, "An image analysis system for dietary assessment and evaluation," *17th IEEE International Conference on Image Processing (ICIP)*, Sept. 2010, pp. 1853 –1856.

[6] M. Bosch, T. Schap, F. Zhu, N. Khanna, C.J. Boushey, and E.J. Delp, "Integrated database system for mobile dietary assessment and analysis," *IEEE International Conference on Multimedia and Expo (ICME)*, July 2011, pp. 1 – 6.

[7] Y. Sato and K. Ikeuchi, "Temporal-color space analysis of reflection," *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, Jun 1993, pp. 570 –576.

[8] S.K. Nayar, X. Fang, and T. Boult, "Separation of reflection components using color and polarization," *International Journal of Computer Vision*, vol. 21, pp. 163–186, February 1997.

[9] S. Lee and R. Bajcsy, "Detection of specularity using color and multiple views," *Proceedings of the Europe conference of Computer Vision*, 1992, vol. 588, pp. 99–114.

[10] S. Lin and H.-Y. Shum, "Separation of diffuse and specular reflection in color images," *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2001, vol. 1, pp. I–341 – I–346.

[11] H.-C. Lee, E.J. Breneman, and C.P. Schulte, "Modeling light reflection for computer color vision," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 12, no. 4, pp. 402 –409, Apr 1990.

[12] H. Farid and E.H. Adelson, "Separating reflections and lighting using independent components analysis," *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 1999.

[13] S. A. Shafer, "Using color to separate reflection components," *Color Research & Application*, vol. 10, no. 4, pp. 210–218, 1985.

[14] G. Klinker, S.A. Shafer, and T. Kanade, "The measurement of highlights in color images," *International Journal of Computer Vision*, vol. 2, pp. 7–32, 1988.

[15] R. Bajcsy, S. W. Lee, and A. Leonardis, "Detection of diffuse and specular interface reflections and inter-reflections by color image segmentation," *International Journal of Computer Vision*, pp. 241–272, 1996.

[16] A.J. Bell and T.J. Sejnowski, "An information-maximization approach to blind separation and blind deconvolution," *Neural Computation*, vol. 7, pp. 1129 – 1159, 1995.

[17] A. Hyvarinen, J. Karhunen, and E. Oja, *Independent Component Analysis*, 2001.

[18] C. Jutten and J. Herault, "Blind separation of sources, part I: An adaptive algorithm based on neuromimetic architecture," *Signal Processing*, vol. 24, pp. 1 – 10, 1991.

[19] J. Shi and J. Malik, "Normalized cuts and image segmentation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 22, no. 8, pp. 888 –905, Aug 2000.