

Analytical survey of highlight detection in color and spectral images

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Abstract. Detection of highlights is a prominent issue in computer vision, graphics and image processing. Applications which require object properties measurement or rendering are affected by specular reflection since the models assume matte diffusing surfaces most of the time. Hence, detection, and sometimes removal, of specular reflection (highlights) in an image may be critical. Several methods are proposed for addressing this issue. In this paper, we present a review and analysis of these techniques in color and spectral images.

Keywords: image analysis, highlights detection, specular reflection, diffuse reflection, spectral imaging.

1 Introduction

The process of extracting information from an image, and its transformation into a useful representation, enables the description of intrinsic characteristics of objects in the scene. Barrow *et al.* [1] introduced the term "intrinsic images" and suggested that the function of the human visual system at its earlier stage is to determine the orientation of the illumination and the surface being observed. The authors describe such details of scenes in term of shading and reflectance images, which are collectively denoted as intrinsic images. There are other intrinsic properties as well, including shading, reflectance, diffuse reflection components and specular reflection components. Diffuse reflection is caused by scattering of light in all directions after hitting the surface, while specular reflection occurs when incident light is reflected in a single direction. Lee *et al.* [2] presented a neutral interface reflection model by examining the light reflection problem through the use of bidirectional spectral-reflectance distribution function (BSRDF) for specifying both incident and reflected beam geometry. They proposed that specular reflection is identical to scene illuminant in color while diffuse reflection contains the intrinsic properties of the surface. There can be significant variations in appearance of a surface in presence of specular reflection, and they appear as an additional surface property which is not intrinsic [3][4].

We are interested in the detection of specular reflection in images. Several computer vision applications such as 3D reconstruction, object detection, recognition, target tracking, and dichromatic editing use the intrinsic information and

are mostly based on the assumption of the surfaces having perfect diffusion. In most of such algorithms, specular reflections and highlights are termed as outliers [5]. However, the presence of specular reflection is unavoidable in most of the real world scenes since the materials and surfaces not only possess diffuse reflection but also show specular reflections, which is explained in the Dichromatic Illumination Model (DIM) [6]. Hence, the assumption of absence of specular reflection for such algorithms introduce constraints and reduce their robustness. There is a loss of details in case of specular reflection, for example texture and color of surface being observed. Highlight removal is often considered as an inpainting problem [7–10]. This methodology is implemented after identification of highlights. In this paper, we discuss the methods for highlight detection. Discussion about removal of specular highlights is out of scope of this paper.

As an example, Figure 1 shows an image of a printed circuit board. The information about connectivity of the circuit is totally washed out in the area which is under direct specular reflection. In addition, there are highlight spots on the metallic surfaces of diodes and resistors. Such spots follow the DIM and create ambiguity concerning the intrinsic characteristics of the object surface. It may thus be desirable to remove the effect of highlights from the image for recovery of information.

Highlight detection algorithms can be classified into various categories on the basis of data being used for input. For color images, we propose two major categories, namely the *single-image* and *multi-images* based techniques, presented in Section 2 and 3, respectively. Furthermore, a relatively recent development in imaging technology is spectral imaging. The problem of specular highlights occurs also in spectral images, therefore we have included it in this review as another category (Section 4). However, this review focuses only on close range

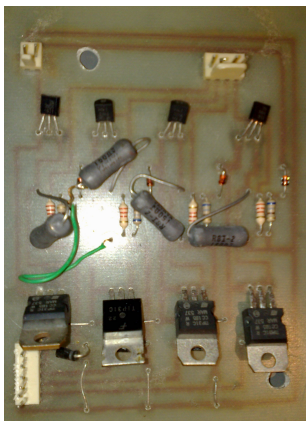


Fig. 1. Image of printed circuit board with transistors, resistors and diodes. Specular highlights can be observed in the highly saturated areas, where it washes out the information. In addition, specular spots are also observed on the metallic parts and resistors.

spectral imaging and does not address remote sensing images. In Section 5, we discuss and compare key features of the presented algorithms, before concluding.

2 Single color image based techniques

We have defined two major categories of algorithms to detect and remove specularities in a single color image. Those categories use either the color space analysis, or spatial information analysis.

The techniques based on color space analysis treat an image pixel by pixel. Klinker *et al.* [11] classified color pixels in the categories of *diffuse*, *highlight* and *saturated* pixels. A diffuse pixel is defined as a pixel containing only the body reflectance (although the color of body is influenced by scene illuminant), a highlight pixel contain both body and specular reflections while a saturated pixel is created when a highlight pixel exceeds the maximum measurable light intensity of camera sensor. Klinker *et al.* [11] analyzed the color histogram and observed that the specular and diffuse components from a uniform surface form a skewed T shape. To separate these components, convex polygon fitting technique is used in their work. Linking color space with DIM [6] is also proposed [12][13]. This color information is used to separate reflection components by fitting it into a dichromatic plane.

Transformation into other color spaces for detection of specularities is also a technique where the characteristics of an adequate color space are exploited. Schlüns and Teschner [14][15] transformed the image from RGB to Y'U'V' color space. Bajcsy *et al.* [16] proposed S-space for analysis of variation in color of objects. There are three orthogonal basis functions in S space named S_0 , S_1 and S_2 . The S_0 basis function corresponds to specular reflection in S space. A data-driven color space called SUV color space was introduced by Mallick *et al.* [17]. Yang *et al.* [18] proposed Ch-CV space. This color space is spanned by maximum chromaticity (Ch) and the coefficient of variation (CV) in RGB. Yang *et al.* [19] proposed separation of specular and diffuse components in HSI color space as further improvement in their already proposed Ch-CV space. Recently, Akashia and Okatani [20] proposed an optimization technique for sparse non-negative matrix factorization for the identification of specular reflections in an image.

In spatial information based techniques, detection of specularities is performed through the use of local information in an image. Tan *et al.* [21] introduced Maximum Chromaticity-Intensity Space to differentiate between the maximum intensity and maximum chromaticity in an image. A pseudo-diffuse component image is created, which is later utilized for separation of specular reflection from the image. The ratio of intensities and colors amongst neighbouring pixels is preserved in the pseudo-diffuse image and is called the specular free image. The specular free image is obtained by Yoon *et al.* [22] through subtracting the minimum value for each channel from the input image. Shen and Cai [23] introduced a modified specular free image by adding an offset to the subtraction method provided in [22]. This offset can either be constant for the whole image [24] or can be varying for each pixel [23]. In [4], intensity logarithm-

mic differentiation is used on both the specular-free and the input image for determination of diffuse pixels. Using this method, performance of the technique of creation of specularly free image is improved for highly textured surfaces. However, the position of highlights should be known for applying this method. Liu *et al.* [25] proposed the preservation of surface color saturation by initially producing a specular free image and then increasing the achromatic component of diffuse chromaticity. It is important to note that in all the specularly free image creation techniques, the input image is normalized for illuminant. Hence, the illuminant should either be known or should be estimated first before applying those techniques.

Yang *et al.* [26] [27] treat the specular pixels as noise and use a bilateral filter for smoothing the maximum fraction of color components. In this way, the noise caused by specular pixels is eliminated. Kim *et al.* [28] observed that a diffuse pixel has low intensity in, at least, one channel. They called it the "*dark channel*" and proposed that the dark channel of an image contains no specular reflection. Their technique uses a maximum a-posteriori formulation that helps in the recovery of specular reflection and chromaticity. An *et al.* [29] proposed the pure diffuse pixel distribution model. This model is built on the assumption that there is at-least one purely diffuse pixel for each material in the scene. Shen and Zheng [30] assumed that some area of a surface contain only the diffuse reflection. They define the range value for an image as maximum minus minimum intensity for a surface and observed that the intensity ratio between maximum value of a pixel and range value is independent of the geometry of the surface. With the assumption for certain pixels to be diffuse, specular components from remaining pixels are computed through their proposed model.

Highlight detection techniques based on a single color image are practical as they do not require any additional hardware and data. However a problem associated with such algorithms is that they rely on image statistics and are based on strong prior assumptions. Therefore, such methods are not robust for change in imaging environment but works reasonably well when the required conditions are fulfilled.

3 Multiple images based techniques

The use of multiple images for separation of reflectance components from the scene is proposed in a number of studies. Since highlights are not intrinsic properties of an image, they can occur at any point and are dependant on the viewing angle. The direction of illumination also has its impact on the location of highlight spots. A surface area of an image which is affected by highlight in one image can appear as a diffuse surface if the viewing angle, or the illumination direction is changed. Based on this phenomenon, multiple images based highlight removal techniques are proposed in the literature, which require a number of images, captured using different imaging conditions.

Lee and Bajcsy [31] proposed the use of Lambertian consistency, which states that the Lambertian reflection does not vary in brightness and spectral contents

with change in the viewing angle while the specular reflection changes the behaviour. They defined the spectral distance as euclidean distance between two colour points in a three-dimensional space. Minimum spectral distance is calculated to detect the inconsistency in color among two images of same scene but with different viewing angle. Sato and Ikeuchi [32] introduced temporal-color space analysis by using a moving light source. Lin and Shum [33] used different illuminations for the same scene, and then proposed linear basis functions for separating diffuse and specular components. Lin *et al.* [34] used stereo images for the detection of specularities. Weiss [35] acquired an image sequence with varying specularities and used maximum likelihood estimation by assuming that the change in illumination gives rise to sparse filter outputs.

Feris *et al.* [36] used flash images taken with same point of view but different positions of flash for recovering the diffuse component. Agrawal *et al.* [37] proposed a method for image enhancement by using two images of a scene. One is taken with flash and one without flash. Reflection from the flash image is removed by using a gradient projection scheme.

Chen *et al.* [38] reconstructed the specular field by using histograms of the same image but with different intensities. Yang *et al.* [39] proposed statistical methods for removal of specularities from stereo images. They assume non-overlapping highlight regions in their method. Wang *et al.* [40] used three cameras for taking images of transparent plastic package containing tablets. They normalized the acquired images and then generated an image consisting of average intensities of corresponding pixels. In this way, pills are retained with higher intensity while varying regions of specular reflection are removed. Generation of specularity map from video sequence is proposed by Prinnet *et al.* [41]. Recently, Wang *et al.* [42] proposed the use of light field imaging technology for capturing multiple views of a scene and then used that information for detection of specularities in the scene.

Nayar *et al.* [43] noticed that the specular reflection is highly polarized and proposed the use of polarization filter to separate the diffuse and specular reflections. They used a polarization filter by placing it in front of a camera and observed that by rotating the polarization filter, the brightness of diffuse materials is not changed, while the specular reflection is changed, since it is highly polarized, and varies following a cosine function. Polarization based methods are also proposed by Wolff [44, 45], Kim *et al.* [46], Atkinson and Hancock [47, 48], Müller [49], Umeyama and Godin [50], Lamond *et al.* [51] and Zhang *et al.* [52].

Although the above mentioned specularity detection techniques are able to show good performance, the major limitation associated with them is the availability of multiple images of the same scene with varying illumination direction or viewing angle. This limitation causes those techniques to become less practical compared to the approaches which are based on a single image.

4 Spectral image based techniques

Hyperspectral and multispectral imaging has been used extensively for remote sensing. Recently, with advancement in sensor technology, spectral imaging is widely available for imaging of objects at shorter distance. Such imaging comes with the problem of highlights, the same as in the case of color images. However, since spectral images contain more data compared to a color image, therefore highlight detection techniques are not exactly the same.

Bochko and Parkkinen [53] proposed probabilistic principal component analysis for detection of spectral and diffuse parts in images. Fu *et al.* [54] proposed orthogonal subspace projection (OSP) and dichromatic model for specularity-free representation of hyperspectral images. OSP results in projecting the radiance and illumination spectrum being orthogonal to each other in the subspace. In this way, the illuminant spectra is removed from mixed spectra and a spectral image without highlights is obtained. It is important to note that prior information about illuminant is required in this method. Koirala *et al.* [55] proposed spectral unmixing of end-members for separation of specular and diffuse components in spectral images. Spectral end-members consist of pure spectra corresponding to objects in a scene. Spectral unmixing method is widely used in hyperspectral remote sensing where the end-members correspond of pure spectra of land cover classes. In the method by Koirala *et al.* [55], Automated target generation program (ATGP) is employed for selection of end-members. When the scene illuminant is known, then the initial target detected by ATGP is the illuminant spectra. In case of unknown illuminant, a pixel with maximum value along the whole spectra is considered as the initial target. Using constrained energy minimization, the diffuse part of the image is identified.

5 Analysis of various specularly detection methods

In Table 1, we compare the characteristics of various specularly detection techniques. In these tables, different techniques are divided in general categories. The concept behind the technique is briefly defined along with the general assumptions being made. Use of DIM is common in the specularly detection techniques but there are some algorithms that do not use this model, so it is also given in the table. White balancing (WB) and image segmentation (Seg.) is also a constraint in such algorithms. We make analysis of various categories of highlight detection algorithms on the basis of the above expressed factors. Finally, general remarks about strength of those techniques is provided.

Table 1: Comparison of characteristics of highlight removal techniques

Category	Images	Concept	Assumptions	DIM use	WB Req.	Seg. Req.	Strength
Color Histogram Analysis [11][12][13]	Single	Skewed T-shape formation between specular and diffuse components	Lambertian body reflection, Interface reflection is function with a sharp peak around the angle of perfect mirror reflection.	Yes	Yes	Yes	Works well for dielectric materials but not for metals
Dichromatic Illumination based Model [6]	Single	Description of reflected light from a dielectric object as linear combination of object color and highlight	Single Illumination, existence of matte cluster	Yes	Yes	Yes	Works well for dielectric materials but not for metals
Color Space Transformation [14][15][16][17][18][19]	Single	Segmentation of specular regions for obtaining the max. diffuse chromaticity in each segmented region	Single Illumination, each segmented cluster has uniform diffuse chromaticity	Yes	Yes	Yes	Iterative process can be time consuming, Colors are distorted in some algorithms. Overall good result on dielectric materials with single illumination.
Saturation preservation model [25]	Single	Creation of over-saturated diffuse reflectance and then putting the achromatic regions back to the diffuse reflection.	Pure white illuminant	Yes	Yes	No	Color saturation of surface is preserved in this method.
Sparse matrix factorization [20]	Single	Sparse non-negative matrix factorization for separation of specular components.	Single illuminant, presence of diffuse component for every surface	Yes	Yes	No	No assumption about spatial priors.
Pseudo diffuse image [3][4][21]	Single	Dark channel prior.	Pure white illuminant	Yes	Yes	Yes	Color ratio among neighbouring pixels is preserved.
Inpainting technique [7–10]	Single	Removal of highlight part through use of neighbouring pixels info. and inpainting	Single illuminant, presence of diffuse component for every surface	No	Yes	Yes	Preservation of color for dielectric surfaces.

Table 1 – Continued from previous page

Category	Images	Concept	Assumptions	DIM use	WB Req.	Seg. Req.	Strength
Multiple images acquisition [31–42]	Multiple	Highlights behave different when viewing angle or illumination is changed	Points which show specular reflection in one image can behave purely diffuse in another image when viewing condition is changed	Yes	---	---	Efficient detection of highlights when the required conditions and no. of images are available.
Polarization [43–52]	Multiple	Use of polarization filter during image acquisition.	Specular highlights are polarized while diffuse reflections are unpolarized	Yes	No	No	With use of additional hardware (polarization filter), highlights can be detected efficiently.
Orthogonal Sub-space Projection [54]	Spectral	Separation of radiance and illumination spectrum through orthogonal subspace projection	SPD of Illuminant is known.	Yes	Yes	No	With knowledge of a particular illuminant, highlight caused by it can be removed.
PCA [53]	Spectral	Use of probabilistic PCA for separation of specular and diffuse components	Colored objects already segmented, Constant Hue.	Yes	No	Yes	Performs efficient highlight removal if segmentation is already performed.
Spectral unmixing [55]	Spectral	Spectral unmixing method	End-member of highlight part is SPD of illuminant.	Yes	No	No	With the use of a proper spectral segmentation method, highlights can be removed

6 Conclusion

In this paper, we provide a survey of highlight detection algorithms in color and spectral images. In most of the literature, results from detection and removal of highlights is presented qualitatively while comparing with other methods. Although qualitative analysis provide a general overview, quantitative measurement should also be used to provide a fair comparison.

Generally, strong assumptions and priors are used for highlight detection. However, the highlight detection is still able to provide much of the useful information and is therefore a critical issue in image analysis. We also review state-of-the-art on highlight detection in spectral images. There is less work done on it and much is yet to be explored. The amount of spectral information being acquired in spectral imaging can certainly provide benefit for highlight detection and is still an open area of research.

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