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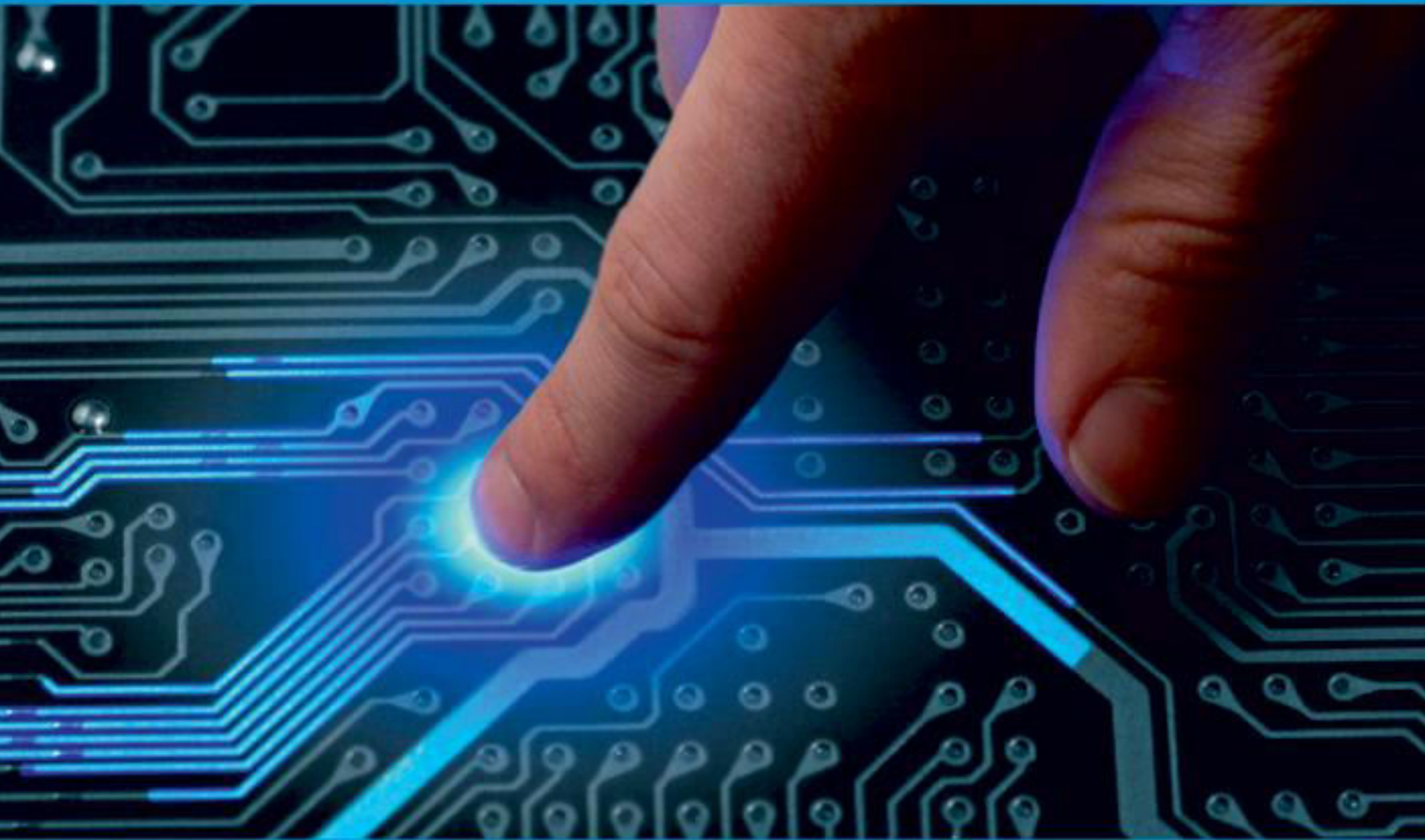

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Highlight Removal from RGB Image using Dichromatic Clustering Model

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ABSTRACT: Quick and higher quality highlight removal from a single natural image is crucial because specular reflection occurs frequently in photographs that lead the recorded color to deviate from its real value. Despite the advancements in highlight reduction over the past few decades, it is still difficult to achieve broad applicability to the huge variety of natural situations. The study offer an analytical highlight removal approach that relies on an L2 chromaticity concept and associated dichromatic modeling to address this issue. By using projection parameters in two sub-bands that are alternately orthogonal to and parallel to the lighting, the research produces the normalized dichromatic method for the pixels having same diffuse color. Specular-free former illumination orthogonal substructure allows for resilient clustering including the explicit standard to adaptively decide the clusteringamount. A feature known as the pure diffuse pixel distribution rule aids in mapping each impacted pixels to its diffuse component in the latter illumination parallel subspace. The suggested method is efficient in that it requires few difficult calculations, which enables it to quickly remove highlights from high-resolution photos. Studies reveal that this approach performs better than others in a range of difficult scenarios.

KEYWORDS: L2 Normalized Dichromatic Model; Specular and Diffuse;Highlight Removal;Specular Reflection; Adaptive Material Clustering;

I. INTRODUCTION

Many vision and graphics tasks[1], including intrinsic image decomposition, color constancy, image segmentation, illumination estimation, and low-light picture augmentation, are made more difficult by the frequent occurrence of specular highlights in real-world images. Thus, the need for efficient specular highlight removal techniques is great. Although a number of techniques have been put forth for eliminating specular highlights, their usefulness is constrained since they frequently generate visually unpleasant results when applied to real-world photos[2]. Recently, some inherent image decomposition techniques for handling real-world photos that also work for removing specular highlights have been developed. However, as most of these methods are based on assumptions that might not be appropriate for photos with specular highlights, they frequently do not effectively remove specular highlights [3].

The combination of the spectral energy dispersion of the illuminating as well as the surface reflectivity yields the spectral energy distribution of the light reflected from an object. The reflected light could be divided into two halves through utilising dichromatic reflection model because of the specular as well as diffuse reflections, respectively. Because specular reflection captures source features and creates a discontinuity in the ubiquitous, object-determined diffuse component, it is challenging for several computer vision applications, including segmentation, detection, and matching. Methods depending on the diffuse component analysis typically dismiss specularities as outliers. Incorporating specularity regions into the analysis is crucial because specular reflections are always present in the actual world as well as capture crucial scene information, surface shape, and source properties[4].

The reflectance behaviors of the scene are described by color information, which is crucial for many computer vision tasks like matching,recognition, segmentation, including intrinsic image retrieval. The color distribution of the scene is captured in the picture of the diffuse reflection, however the image intensities of widely prevalent non-Lambertian surfaces, such those in the specular regions, considerably vary from their true color information. Additionally, there are projects that are focused solely upon the specular component, like form from specular reflection [5]. Therefore, it is crucially important to distinguish the highlight from the diffuse component in photographs of non-Lambertian settings. In this study, an analytical highlight removal approach is proposed that relies on an L2 chromaticity concept and associated dichromatic modeling to address this issue. First, by using projection parameters in

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two sub-bands that are alternately orthogonal to and parallel to the lighting, a normalized dichromatic model is produced for the pixels having a same diffuse color. Second, a feature known as the pure diffuse pixel distribution rule aids in mapping each impacted pixels to its diffuse component within the latter illumination parallel subspace.

Related Works

The study suggest an unique learning strategy using a fully convolutional neural network that automatically and reliably generates the diffuse feature of an image in order to exclude specular highlights. In the GAN framework, researchers established with an adversarial loss upon a discriminative network as well as combine it with a content loss in order to train the generative network. The study applied the discriminator to be a multi-class classification instead of a binary one, in contrast to prior GAN techniques, to uncover more restricting features. By giving the network two more gradient terms, this aids in locating the diffuse manifold. A fictitious dataset that was created to aid in the network's generalization was also produced. However, the network used in this study has failure situations that occur in actual applications. One of the key problems is that mirror surfaces are not handled, which calls for an entirely different characterization of the issue [6].

The study analyzed an existing physical-based linear color segmentation algorithmand a brand-new segmentation algorithm modification. The algorithm is built on a foundation of region adjacency graphs without pre-segmentation. Edge weight functions that are proposed are defined using a linear image model with typical noise. Researchers introduce the color space projective transform as a brand-new pre-processing method for handling shadow and highlight regions more effectively. The resulting method is evaluated on a benchmark dataset made up of 12 recently released natural scene photos and images of 19 natural scenes chosen from the Barnard's DXC-930 SFU dataset. Every image in the dataset has pixel-by-pixel ground truth color segmentation. Strong shadows and overexposed areas are processed well by the algorithm, according to experimental findings. Some shortcomings can be attributed to the model's or the weight function's restrictions [7].

The simultaneous recording of spectral with polarization image dataset is made possible by modern imaging techniques. It is interesting to define the associated image statistics to enable the plan of computational imaging algorithms as well as upccming processing of this data. Researchers specifically present observations for several spectropolarimetric channel correlations. Several publicly accessible databases that have been combined for collaborative processing are the subject of the analysis. Researchers conduct extensive research and analysis on a number of distinct material or reflection type clusters. When compared to spectral channels, polarization channels are noticed to be typically exhibit higher inter-channel correlation. However, in this work, RGB is assumed to be a standard representation for color images, and the discrepancies relating to their spectral properties have been disregarded [8].

The Specular Photometric Stereo (SPS) technique, a variation of Photometric Stereo (PS) that incorporates specular reflection, is presented in the study. Similar to the standard PS, the suggested SPS obtains surface normal by combining photographs of a surface taken under various lighting situations, but it also makes advantage of the specular elements of dark surfaces that reflect small diffuse light. The suggested technology consists of multiple consecutive numerical steps: first, a highly nonlinear specular reflection model is transformed into a nonlinear equation with just one nonlinear parameter, and then the diffuse components are iteratively removed. The standard PS is unable to estimate the normal of dark surfaces, while the proposed SPS could. Synthesized data were used to examine the suggested SPS before it was put to the test on actual surfaces [9].

Many modern feature identification algorithms suffer from performance accuracy paralysis due to the creation of specularity reflection. Specularity removal in real-world imaging circumstances is more difficult when there is no available source of illumination. According to the literature, chromaticity-based reflection removal algorithms work by converting the pixels into the chromaticity-intensity plane and resolving a complex, least-squares issue posed by the dichromatic model. This avoids the dependence of the lighting source. In the article, researchers expand the already used chromaticity-based removal method to the hue-saturation-value color domain and investigate its applicability in the removal of specularity in flash imaging scenarios [10].

II. EXISTING METHOD

In the existing method has the creation of solutions for enhancing current techniques for integration into display systems like TVs. In the past, highlight region detection techniques for digital cameras have been registered for patents. The highlight removal problem has recently been approached using only uncomplicated, simple methods.

III. PROPOSED METHOD

The diffuse chromaticity alone determines the direction delta in the L_2 normalized dichromatic model since it has been orthogonal towards the lighting direction delta and has no connection to the specular element. Each cluster's specular

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highlight can be eliminated by using the direction delta to identify the cluster's pure diffuse pixels. The study has the normalized specular free component delta for each pixel of the input specularly tainted image and the accompanying illumination.

The L_2 Normalized Dichromatic Model

The commonly used dichromatic model is normalized in this study by the L2 norm, and as a result, an orthogonal decomposition approach for the surface appearance is derived. The imaging procedure for a color camera might be stated as follows in Eq.1:

$$c_i(a) = s_1(a)\int \alpha[r1(a,\beta)r2(\beta)r3(\beta)d\beta + s1(a)]\int \alpha[r2(\beta)r3(\beta)d\beta] \quad (1)$$

$c_i(a)$ in this case denotes the intensity of channel i at pixel a, where $a = \{a, b\}$ denotes the 2D location and c denotes the camera channel. The diffuse and specular components, represented by the multi terms upon the right-hand side of the equation, have strengths of $s1(a)$ and $s2(a)$respectively.$r1(\beta)$, $r2(\beta)$,and $r3(\beta)$describe the illumination spectrum, surface reflectance, as well as the camera's spectral reaction of channel$i$, correspondingly. In each phrase, signifies the wavelength with range being.

Eq. 1 can be expressed by writing the pure diffuse component and specular highlight as$d_i(a) = s1(a)\int \alpha\,[r1(a,\beta)r2(\beta)r3(\beta)d\beta]$ and$h_s(a) = s2(a)\int \alpha\,[r1(a,\beta)r2(\beta)r3(\beta)d\beta]$, respectively as given in Eq.2.

$$i(a) = d_i(a) + h_s(a) \quad (2)$$

The chromaticity of the diffuse component's and the specular highlights, respectively, are denoted by the symbols αandμ in Eq.3 and 4.

$$\alpha(a) = d_i(a)/||d_i(a)||f \quad (3)$$

$$\mu(a) = h_s(a)/||h_s(a)||f \quad (4)$$

The orthogonal projection algorithm put out by Chang [32] can be used to carry out the projection process in Eq.5

$$\alpha(a) = x(a)\mu'(a) + y(a)\mu \quad (5)$$

In the end it can be written as shown in Eq.7 after substituting the respective parameters:

$$\gamma'^{(a)^2} + \gamma(a)^2 = 1 \quad (6)$$

Adaptive Highlight Removal

The diffuse chromaticity alone determines the direction, which can be utilized to distinguish between various materials, according to the L2 normalized dichromatic method. The coefficient corresponding towards the direction could be utilized to locate the pure diffuse pixels as well as eliminate the specular highlight in every cluster under the guidance of the pure diffuse pixel rule attribute. As shown in Figure 1, a highlight removal framework is suggested by summing up these attributes in both directions.

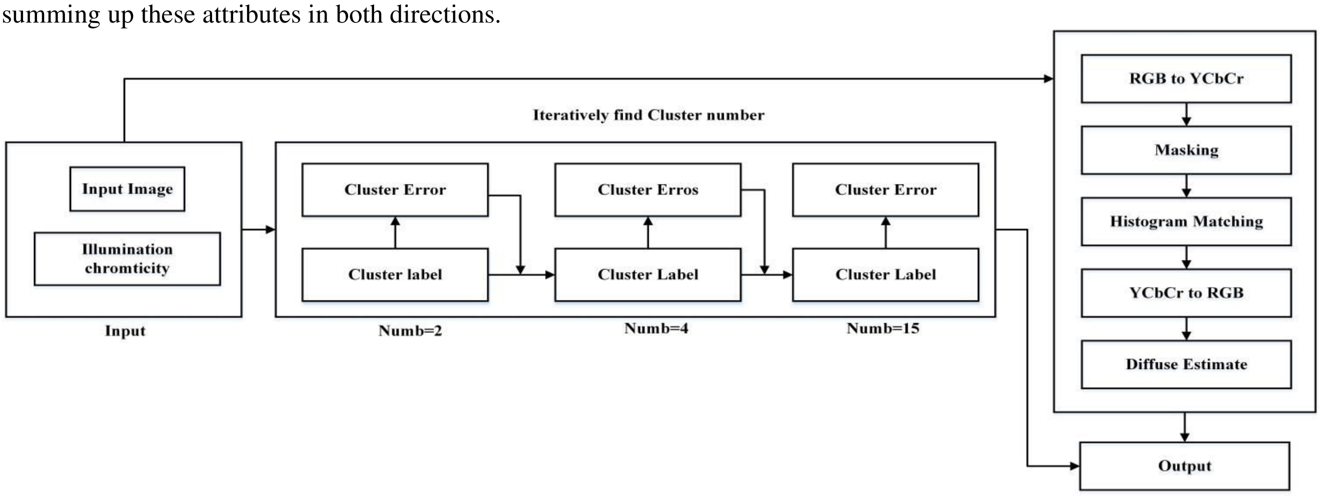

Figure 1: **Highlight Removal approach using adaptive material clustering**

First, obtain the normalized specular-free component appropriate to every pixel utilizing the input specularly contaminated image as well as related lightning (shown in the top-left-block). Then, as shown in the top row, middle column of Figure 1, specular-free clustering by utilizing K-Means is performed throughrising the amount of clusters till converges, using the convergence criterion established from the fitting error towards the techniques parameters in Eq.6. The upper row within the image space and the lower row in the parameter space in the middle column of Figure 1 show the evolution of the clustering techniques. The findings are then displayed on the right-most column after every pixel

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has had its specular as well as diffuse components separated. Materials clustering as well as diffuse element recovery are the two subsequent steps that are covered in detail within the following subsections.

Material Clustering

Due to the effects of specularity, it is challenging towards identify the pixels using the similar diffuse reflectance in the raw space for a picture that has specularity affects. The materials in the lightning orthogonal subspace are clustered to prevent the effects of specularity. This resembles towards the normalized data of pixels with the similar diffuse color but differing specular intensities cluster well. The suggested approach adaptively calculates the number of clusters without losing generality.Starting with a cluster amounts that is no more than the genuine material kinds; it should gradually increase until it achieves the right number. The starting cluster number can typically be set to 1 for safety. Prior to clustering, first project the input image's chromaticity onto the lighting orthogonal subspace in each cycle. Re-project the normalized reflectance into i as well as to obtain coefficients as well as for each cluster after replacing with the cluster center i. According to Eq.6, i effectively reflect this cluster if the sum of squares of the coefficients is near to 1 or located upon a unit circle. On the other hand, it is assumed that the pre-determined cluster quantity is inaccurate if the number of pixels along coefficients that deviate from the unit circle exceeds the specified threshold (for instance, 10%). The threshold is set to be 0.1 experimentally and utilize the overall fitting error to the unit circle as the clustering precision. Increase the cluster through the amount of clusters that did not fulfill the precision criteria after examining every cluster, then move on to the following iteration. The iteration will be terminated, while the cluster number stops rising. Additionally, the distribution of the relevant fitting error towards the suggested unit circle model is shown. For the majority of scenarios, the method experimentally converges after 5 iterations.

Pixel Diffuse based Component Recovering

Theoretically, the least value corresponds to the smallest parallel component that will represent the pure diffuse pixels in everycluster(a). However, noise is always present in real-world situations, and pixels falling near the initial peak of the histogram are viewed as fully diffuse. It is simple to take out the specular highlight once you have located the pure diffuse pixels in each cluster. Finding the coefficients $x(a)$ and $y(a)$along $\alpha(a)$ and $\mu(a)$is identical to solving the issue of recovering the diffuse component from Eq.5. The issue can be further simplified by determining the ratio and calculated by directly projecting the values on corresponding equations. On the one hand, this ratio is independent of the strength of the specular reflection for pixels with the same diffuse component. However, for pure diffuse pixels, the ratiosare similar with each other. As a result, using the known pure diffuse pixels, it is possible to directly determine the ratio in each cluster.

Result

In the input images, the highlights like specular reflection are removed using image processing pipelines. The input image is given in Figure 2.Histogram matching is employed to specify the intensity transformation from lack of pseudo specular image representation. As well the histogram of the original input mage is given in Figure 3.

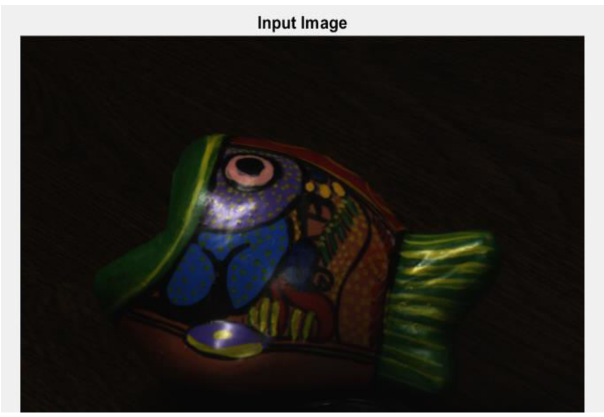

Figure 2: **Input image**

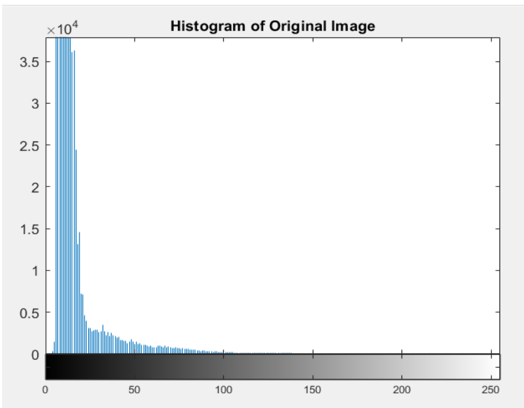

Figure 3: **Histogram of the input image**

Clustering image is based on the intensity transformation with highlight removal of original image. Figure 4 represents the clustered image. Histogram matching highlights of clustering image specify the unit transformation input. Histogram of clustered image is depicted in Figure 5.

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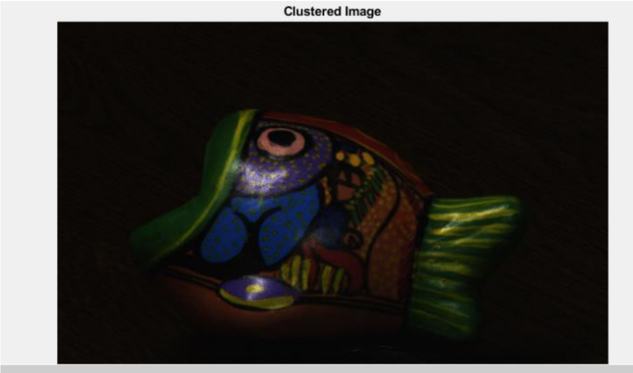

Figure 4: **Clustered image**

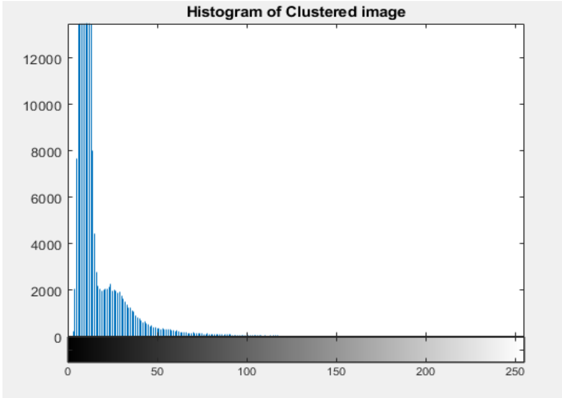

Figure 5: **Histogram of the Clustered image**

Reflection of dichromatic method as well as operates using the histogram matching in the YCbCr color space. Figure 6 shows the YCbCr image. Masked image is the some of the pixel intensity values. Figure 7 shows the masked image.

Figure 4: **YCbCR image**

Figure 5: **Masked image**

Specular reflectance highlight component has been removed from the input image which is given in Figure 6. Histogram with the reflectance components according to the specificity of output image is shown in Figure 7.

Figure 6: **Highlight removed output image**

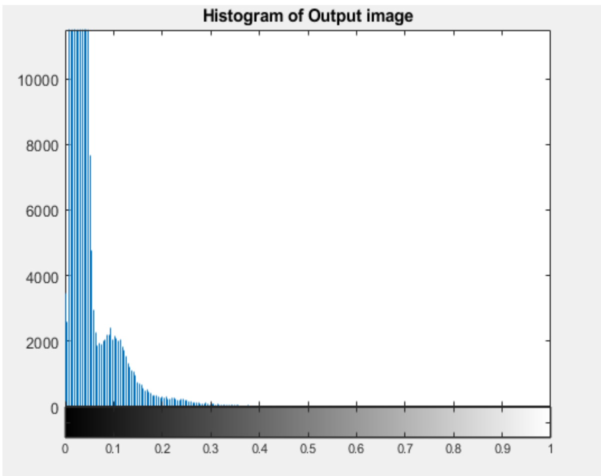

Figure 7: **Histogram of the output image**

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A single picture highlight removal technique that is up to date with modern improvements is suggested. It is the most straightforward proposal so far and has a solid basis in a physical reflection model. Its fundamental principle is histogram matching of an image representation within a perceptually coded color space. The findings revealed that the suggested approach finally outperformed the majority of self- and peer-reported criteria and demonstrated itself to be a quick as well as valuable contribution.

Comparison of the proposed method

The highlight removal approach is highly efficient in terms of both storage and processing because it does not require sophisticated computations. On a workstation with the Intel Xeon 2.27 GHz CPU running 64-bit Windows 7, and tested the efficiency. Processing a photograph with a size of 500 by 600 pixels typically takes 0.02 seconds, with some little fluctuation because of various types of materials used in numerous images. In this method, the clustering module takes the longest. It could easily handle such scenarios using a down sampling method, even though the K-Means clustering that has been chosen with slow downed at very higher resolution. To be more precise first reduce the size of the original image to one that still contains all of its components (for example, 200 200 pixels). After conducting material clustering on the low resolution image using the suggested method, the diffuse chromaticity of each cluster is applied. The cluster name and associated diffuse chromaticity are then allocated to every pixel in the higher resolution input image as thatclustering having the strongest correlation in the specular-free space.

Table1: **Accuracy of proposed and existing method**

Technique	Accuracy
Intensity ratio	88.4%
Bilateral filtering	90.2%
Clustering model	97.7%

The proposed method is contrasted with the existing models of highlight removal using intensity ratio [11] and Bilateral Filtering[12] but then the accuracy of the proposed method is 97.% which is higher than the existing other two models which is shown in the above Table 1. The data show that, even though the proposed algorithm was created using Matlab, it is still a little bit quicker than the other two methods created using C++. The efficiency superiority, which is a result of the down sampling method, is more obvious at greater resolution.

IV. CONCLUSION

In order to distinguish the diffuse from the specular components, this work defines the L_2 normalized dichromatic method as well as derives a rigorous devising. The strategy is capable of handling a wide range of problems that are intractable by the other techniques because neither strong assumptions nor mathematical approximations are required. Additionally, the suggested method only calls for a small number of difficult calculations, enabling quick processing. Studies reveal that this approach performs better than others with 97.7% of accuracy in a range of difficult scenarios. It is intended to expand the current method for removing specularity from videos in future research. Using temporal redundancy would improve performance and efficiency even more. The sparse immediate modifications would increase forcefulness to distortion, for starters. The processing of the other would be sped up by the modest difference in material types across neighboring frames as the study does not have to begin with a single cluster. The parting of diffuse as well as specular mechanisms under uncertain light is also achievable by utilising few priors into account that includes the sparsity of constituents in the scene. Additionally, highlight reduction under several illuminations of various hues is intriguing and merits research.

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