# Single Image Reflection Removal

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**Received: 12 June 2018 Accepted: 24 October 2018**

## Abstract

This paper presents a proposed algorithm for removing undesired reflections from a single mixture image captured in front of transparent glass mediums. The proposed algorithm separates the single input image into background layer (actual scene) and the reflection layer by clustering mixture image pixels, using the prior knowledge that the background edges are of larger magnitude than reflection edges and the model of dichromatic reflection. Experimental results on real-world images proved that the proposed algorithm gets a result of the background image with reflections removed as much as possible. A quantitative and visual quality comparison between the proposed algorithm and state of the art algorithms is performed.

**Keywords:** reflection removal, specular reflection, mixture image**,** K-means and background layer.

## ازالة الانعكاس من الصور باستخدام صورة واحدة

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## الخلاصــة

هذا البحث يقدم خوارزمية مقترحة لازالة الانعكاسات من صورة مركبة واحدة تم التقاطها من خلال وسط زجاجي شفاف. الخوارزمية المقترحة تقوم بفصل الصورة المركبة الى صورة المشهد الاساسي وصورة الانعكاس باستخدام تقنية التجميع والنموذج الثنائي الالوان.

والنتائج التجريبية على الصور الحقيقية اثبتت امكانية الخوارزمية المقترحة على تقديم نتائج لصور المشهد الاساسي خالية من الانعكاسات قدر الامكان والتي تم مقارنتها مع الخوارزميات الحديثة مرئياً وقياسياً.

**الكلمات المفتاحية:** ازالة الانعكاس، انعكاس البريق او اللمعان، صورة مركبة، تقنية التجميع K-means وطبقة المشهد الاساسي.

## Introduction

Recently handheld smart devices such as smartphones and tablets are used for capturing scenes under nonoptimal imaging conditions, forcing people to capture photos through reflecting mediums, this leads to undesired reflections and loss of information in the captured image [1]. Remove reflections is a useful preprocessing step in computer vision to remove unwanted information from the image to be enhanced and analyzed [2].

The captured image through glass panes or windows is a mixture of two sources, a scene behind it (background layer) and a reflection of a scene on the same side of it (reflection layer), the goal is to keep the transmission scene and remove reflection information from the original image simultaneously [3]. The mixture images are characterizing by low quality, depress human recognition and decrease the performance of image segmentation and object detection algorithms. Therefore, these images need to be pretreated to remove reflection. In recent years this field has been of much interest [4]. The reflections impression can be minimized by utilizing specific hardware, e.g. experienced photographers use polarizing filters to reduce reflection artifacts [5].

To deal with reflection removal problem different methods have been introduced. Some of them utilized more than one input image to make the problem easier to fix by using a series of images caused by a camera movement [6]. Another type of methods used a single superimposed image to separate reflections as [7] that is based on natural image priors such as sparsity prior, or the reflection edges less smooth than background edges suggested by [8] to separate reflection. From a computational perspective, traditional imaging models suppose that the captured mixture image $\boldsymbol{I}$ is a linear combination of a background layer $\boldsymbol{BL}$ and a reflection layer $\boldsymbol{RL}$,

$$\boldsymbol{I} = \boldsymbol{BL} + \boldsymbol{RL} \tag{1}$$

The separation of ***BL*** and ***RL*** from a single mixture input ***I,*** is as yet a challenging problem due to derive two scenes from one an observed mixture image. Various methods have been suggested to handle this problem by making assumptions to make the problem tractable, but the assumptions have been restricted to special cases and are not applicable to real-world images [9, 10]. A single image-based approaches is practical significance since in more cases the user does not have more than one image and considered a limited efficiency because of the highly difficult nature of the problem, further, the approaches suggested yet are often computationally ineffective [5].

Clustering is a method of gathering objects into clusters that the analogous ones take up the same group and the different ones into another group. The broad diversity of clustering applications in education, industry, and agriculture has increased the importance of clustering [11]. Allocating surveillances to groups **(**clusters**)** is the aim of cluster analysis, where surveillances in a group are similar to one another regarding features of interest [12]. The K-Means algorithm is a famous splitting approach for clustering. Euclidean distance is used to measure the nearness of the data in the K-Means to groups the data [13]. The mean value of objects in the cluster is used in k-means to represent the cluster, to divide a collection of N objects into K cluster the likeness of the inter-cluster must be low while the likeness of the intra-cluster similarity is high [14]. This paper proposes an algorithm automatically classifies the edges of a single mixture image into reflection and concerning object (background) by using K-Means clustering. The proposed algorithm can successfully separate the reflection and transmission layers taking into consideration high illumination cases.

## Related Work

As reflection removal is actually an underdetermined problem, assumptions and prior knowledge are required to make the problem flexible to obtain any level of success. Most popular methods to remove reflections used multiple input images under various conditions [10]. Authors in [15, 16] measured the motion for images captured from different viewpoints by using Scale Invariant Feature Transform flow (SIFT-flow) to classify the edges as reflection edges or background edges in order to separate the layers. The work of [17] used several images captured with different polarization angles and based on a physical reflection model to estimate the reflection layer. Also, in [18] a constraint on the disparity map is imposed that preserves the sharpness of the background layer and smoothing the reflection layer, utilized the truth that the reflections differ in multiple images taken from different viewpoints. In a like manner, some methods used video sequences as in [19] where the average image prior and the region-based optimization technique is proposed to remove the reflection on the windscreen from in vehicle black box videos.

It may be difficult to apply these methods practically because multiple images taken from experimental settings that are controlled are not always available [10].

Reflection removal methods from a single image have attracted increasing interest because of its practical importance, where the user in most cases will not be able to obtain multiple images, although the problem is more difficult than multiple image methods [5]. Some existing works as in [20, 7] are based on a Laplacian mixture prior over the image gradients in solving a constrained optimization problem to classify transmission and reflection edges, and in [8] values of gradient are utilized indirect manner, where the separated images are reconstructed from the classified gradients that based on the smoothness constraint in the classification of gradients in the superimposed image. The two layers (transmission and reflection) are extracted automatically in [21] by optimizing an objective function that imposes a sparse gradient prior over the transmission layer and a smooth gradient prior over the reflection layer. Also ghosting artifacts are exploited in [22] to separate the layers using the GMM (Gaussian Mixture Model) for regularization, and authors in [23] generated transmission and reflection edge maps by computing the depth of field (DOF) per pixel with the use of Kullback Leibler (KL) divergence, Recently, the Laplacian data fidelity term is used in [5] for optimization problem to suppress reflections.

## Proposal Algorithm

The input to the proposal is a single mixture image taken in front of glass panes or windows, removing reflections from it requires separating the input into the background layer and the reflection layer that is a massively hard problem, therefore additional information or priors are required. This paper proposes edge classification to either background or reflection edges based on that transmission edges are of larger magnitude than reflection edges; which is a true fact in real life scenarios. The proposed algorithm exploits the natural image prior (gradient sparsity prior), where the background and reflection edges are estimated by clustering mixture gradient pixels and automatically labels mixture image gradients as either reflection or background using K-mean clustering. Algorithm 1 describes the background and reflection edges estimation by K-mean clustering. The algorithm is started by computing the gradient of input (I), then it is grouped into two clusters (background and reflection, k=2) by K-mean clustering method, where the pixels of low gradient values are grouped to form the estimated reflection image and the pixels of high gradient values are grouped to form the estimated background image.

**Algorithm 1:** Background and Reflection layer estimation to remove reflection from a single mixture image

```
Input: input image I;

Output: Estimation of Background Layer image (BLI) and Reflective Layer image (RLI) of the input
image I;

Initialization: k ⟵ 2; // number of clusters.

1-  GRI ⟵ Compute gradient for I; // GRI=sqrt (g²x + g²y), gx, gy: vertical and horizontal derivative.

2-  Lc ⟵ Compute K-mean clustering for GRI into k clusters; // Lc: Labeled clusters.

3-    For i=1 to row (GRI) do
          For j=1 to col (GRI) do
              If Lc (GRI (i, j)) =1 then
                RF (i, j) ⟵ 1;
              end if
              If Lc (GRI (i, j)) =2 then
                BG (i, j) ⟵ 1;
              end if
          end for
      end for

4-    For i=1 to row (RF) do
          For j=1 to col (RF) do
              If RF (i, j) =1 then
                RLI (i, j) ⟵ GRI(i, j);
              else
                RLI (i, j) ⟵ 0;
              end if
          end for
      end for
```

```
5-   For i=1 to row (BG) do
         For j=1 to col (BG) do
             If BG (i, j) =1 then
                BLI (i, j) ← GRI (i, j);
             else
                BLI (i, j) ← 0;
             end if
         end for
     end for
```

The real-world scenarios indicate that background edges are high intensity than reflection edges, but sometimes reflection edges have higher intensities such as specular reflections due to light sources. Therefore, pixel classification into the background layer or reflection layer will be inaccurate. The proposal aims to obtain the clearer background layer via estimating specular reflection pixels that are located in the background layer according to algorithm 1and converted them to the reflection layer. The proposed algorithm is based on the error analysis of chromaticity in [24] to estimate and convert specular pixels to the reflection layer.

In the dichromatic reflection model, V(p) is the color of a pixel p which a linear combination of diffuse reflection component with body color Vb and specular reflection component with surface color Vs:

$$\mathbf{V(p) = \alpha(p)Vb + \beta(p)Vs} \tag{2}$$

The coefficients of the diffuse and specular reflection components are α(p) and β(p), respectively. The illuminant color is obtained by imaging a white object surface. The color of each pixel is normalized with respect to the illuminant color and then rescaled to the range 0-255. This operation makes the surface color become pure white.

Algorithm 2 describes the estimation of the specular reflection pixels and converts them to the reflection layer. The algorithm is applied the method in [24] on the input mixture (I) to get image (SPI) contains regions that are close to white color represents the estimated specular reflections, in step 2 the gradient of the (SPI) image is computed to specify specular reflection pixel using threshold (thr), where the gradient value of the pixel is equal or exceed the threshold is labeled as specular pixel and takes the value (1) in the (SR) matrix or image. The binary matrix (SR) is used in the final step to modify the output of Algorithm 1 (background layer BLI and reflection layer RLI) by removing pixels from the background layer that corresponding to the value (1) in the (SR) and adding them to the reflection layer.

**Algorithm 2:** Specular Reflection pixels estimation from a single mixture image.

```
Input: input image I, GRI, BLI, RLI;

Output: Background Layer image (BLI) and Reflective Layer image (RLI) with estimation of specular
reflection pixels;

1-  SPI  ⟵ apply method [24] on (I) to estimate specular reflection pixels;

2-  GRSI  ⟵ Compute gradient for SPI; // GRSI=sqrt (g²x + g²y), gx, gy: vertical and horizontal derivative

3-    For i=1 to row (GRSI) do
          For j=1 to col (GRSI) do
              If (GRSI (i, j)) >= thr then// thr: threshold
                 SR (i, j) ⟵ 1;
              else
                 SR (i, j) ⟵ 0;
              end if
           end for
       end for

4-    For i=1 to row (SR) do
          For j=1 to col (SR) do
              If SR (i, j) =1 then
                 RLI (i, j) ⟵ GRI(i,j);
                 BLI (i, j) ⟵ 0;
              end if
          end for
      end for
```

Then the output of algorithm 2 is the reflection and background edges (RLI, BLI) that are used to reconstruct the reflection and background images utilizing the objective function of the proposal in [7], where the distribution model of gradient in natural images is used for restoration in the gradient domain, which is as follows:

$$\mathbf{J}(\mathbf{I_{BLI}}) = \sum_{\mathbf{i,k}} \mathbf{p}(\mathbf{f_{i,k}} . \mathbf{I_{BLI}}) + \mathbf{p}(\mathbf{f_{i,k}} . (\mathbf{I} - \mathbf{I_{BLI}})) + \boldsymbol{\gamma} \sum_{\mathbf{i} \in \mathbf{EB,k}} \mathbf{p}(\mathbf{f_{i,k}} . \mathbf{I_{BLI}} - \mathbf{f_{i,k}} . \mathbf{I}) + \boldsymbol{\gamma} \sum_{\mathbf{i} \in \mathbf{ER,k}} \mathbf{p}(\mathbf{f_{i,k}} . \mathbf{I_{BLI}}) \quad \mathbf{(3)}$$

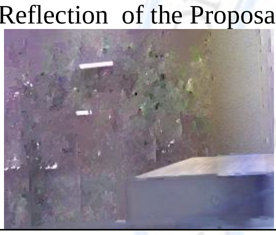
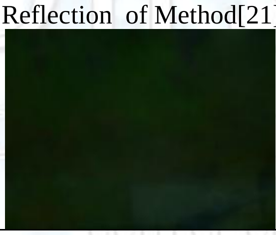
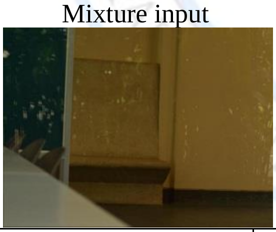
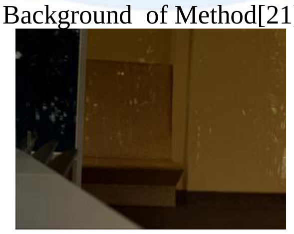
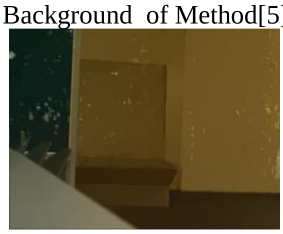
Where $f_{i,k}$ is the k-th derivative filter. $E_B$ (BLI) and $E_R$ (RLI) are two sets of background and reflection edges estimated before, respectively. The first term ensures the sparsity of gradients of the two layers. The last two terms enforce the agreement with the labeled gradients.

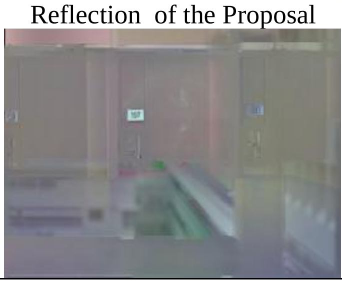
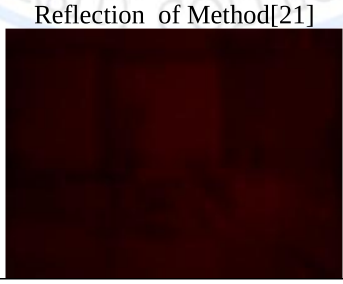
## Results

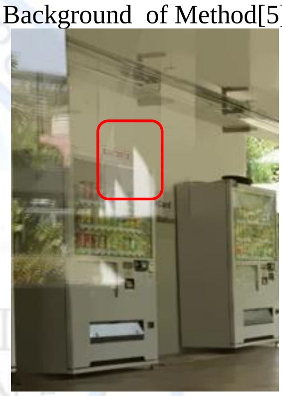
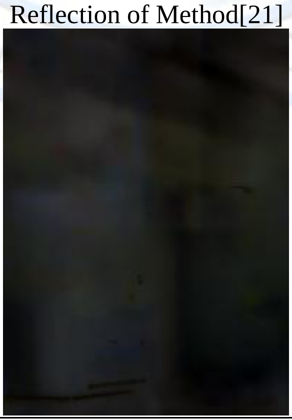
This section presents the experimental results of the proposed algorithm which is performed on a single real-world mixture. The effectiveness of the proposal is tested using $SIR^2$ dataset [25]. The $SIR^2$ dataset contains controlled and wild scenes; a wild scene contains real-world objects of complex reflectance with various distances and scales, and different illuminations. The night scenes bring different levels of difficulty to the reflection removal algorithms since they contain much stronger reflections. But the controlled scene includes only flat objects or objects with similar scales and captured in an indoor office environment. To show the performance of the proposed algorithm, it is applied to the wild scenes which contain different depth and distances in addition to various natural environment illumination. The proposed algorithm is compared with two single removal reflection methods proposed in [21, 5] using quantitative evaluation and visual quality comparison. Four quantitative metrics are adopted (sLMSE: similarity Local Mean square Error, NCC: Normalized Cross Correlation, SSIM: Structural Similarity and SI: Structural Index) that are used by [25], in addition to Peak Signal to Noise Ratio (PSNR). The threshold value (thr) is set to (0.5) empirically.

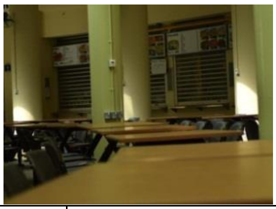
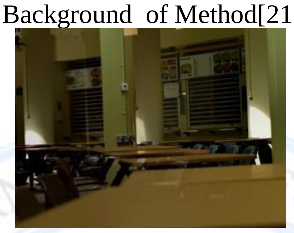
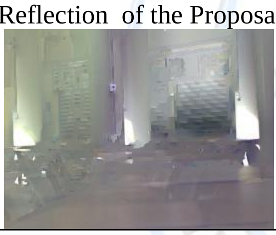
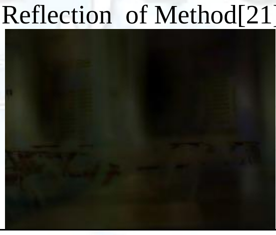
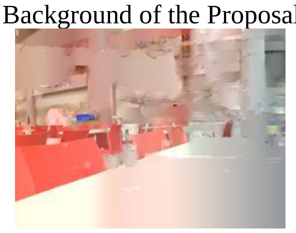
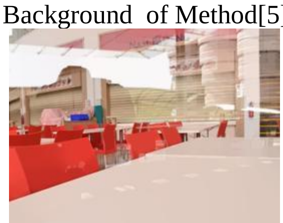
Figure 1 shows a comparison between the results of the proposed algorithm and the methods in [21, 5] with error metrics between the resulted background layer and the ground truth of the mixture. In terms of quantitative evaluation, the results in Figure 1 proves that the proposed algorithm provides an accept separation of the two layers and better performance than the two methods in [21, 5] in some examples according to the metrics as displayed below the background layer.

From the visual quality comparison, one can observe that the proposed algorithm can remove most of the specular reflections that cannot be removed by methods in [21, 5] that are framed in red, provide adequate reflection layer and keep colors unchanged and show the general details clearly. It is evident from Figure1, that the proposed algorithm is successful in the separation of the background and reflection layers in a clearer background.

<table>
<tr><td>Mixture input<br></td><td colspan="2">Ground truth<br></td></tr>
<tr><td>Background of the Proposal<br><br>sLmse=0.9845 NCC=0.7655<br>Mssim=0.9994 SI=0.7517<br>PSNR= 18.1068</td><td>Background of Method[21]<br><br>sLmse=0.9933 NCC=0.9260<br>Mssim=0.9997 SI=0.9916<br>PSNR= 21.7386</td><td>Background of Method[5]<br><br>sLmse=0.9954 NCC=0.9486<br>Mssim=0.9998 SI=0.9859<br>PSNR= 23.3574</td></tr>
<tr><td colspan="3">The proposal can remove most of the specular reflections that cannot be removed by methods in [21,5] that are framed in red, in addition to recover the details of the background layer more clearly and keep colors unchanged.</td></tr>
<tr><td>Reflection of the Proposal<br></td><td>Reflection of Method[21]<br></td><td>Reflection of Method[5]<br>Not available</td></tr>
<tr><td colspan="3">An adequate reflection layer is recovered by the proposal with a bright color compared with method in [21] that look like darker.</td></tr>
<tr><td>Mixture input<br></td><td colspan="2">Ground truth<br></td></tr>
<tr><td>Background of the Proposal<br><br>sLmse=0.9969* NCC=0.9252<br>Mssim=0.9999* SI=0.9767**<br>PSNR= 25.0409*</td><td>Background of Method[21]<br><br>sLmse=0.9932* NCC=0.9690<br>Mssim=0.9997* SI=0.9738*<br>PSNR= 21.6714*</td><td>Background of Method[5]<br><br>sLmse=0.9989 NCC=0.9768<br>Mssim=1.0000 SI=0.9637*<br>PSNR= 29.6639</td></tr>
<tr><td colspan="3">The bold numbers indicate the better performance for the proposal than the two methods in [21,5]. The proposal recovers the whole background image with better quality and removes the reflections more effectively.</td></tr>
</table>

| | | |
|---|---|---|
| Reflection of the Proposal  | Reflection of Method[21]  | Reflection of Method[5] Not available |
| The proposal can recover adequate reflection layer with a bright color compared with method in [21] that look like darker. | | |
| Mixture input  | Groundtruth  | |
| Background of the Proposal  sLmse=**0.9891*** NCC=**0.8498*** Mssim=**0.9996*** SI=0.9183 PSNR= **19.6358*** | Background of Method[21]  sLmse=0.9796* NCC=0.7219* Mssim=0.9992* SI=0.9820 PSNR= 16.9103* | Background of Method[5]  sLmse=0.9897 NCC=0.8585 Mssim=0.9996 SI=0.9401 PSNR= 19.8731 |
| The bold numbers indicate the better performance for the proposal that recovers the whole background layer with better quality and keep colors unchanged than the method in [21]. | | |
| Reflection of the Proposal  | Reflection of Method[21]  | Reflection of Method[5] Not available |
| The proposal can recover adequate reflection layer with a more details and a bright color compared with method in [21] that look like darker. | | |

<table>
<tr><td colspan="2">Mixture input<br></td><td>Ground truth<br></td></tr>
<tr><td>Background of the Proposal<br><br>sLmse=**0.9835****<br>NCC=**0.7181****<br>Mssim=**0.9994**** SI=0.9344<br>PSNR= **17.8141****</td><td>Background of Method[21]<br><br>sLmse=0.9829* NCC=0.7180*<br>Mssim=0.9993 SI=0.9977<br>PSNR= 17.6728*</td><td>Background of Method[5]<br><br>sLmse=0.9798*<br>NCC=0.7109*<br>Mssim=0.9992* SI=0.9959<br>PSNR= 16.9510*</td></tr>
<tr><td colspan="3">The bold numbers indicate the better performance for the proposal and remove most of the specular reflections that cannot be removed by methods in [21,5] that are framed in red.</td></tr>
<tr><td>Reflection of the Proposal<br></td><td>Reflection of Method[21]<br></td><td>Reflection of Method[5]<br>Not available</td></tr>
<tr><td colspan="3">The proposal can recover adequate reflection layer with clear specular reflections compared with method in [21] that look like darker.</td></tr>
</table>

<table>
<tr><td colspan="2">Mixture input<br></td><td>Ground truth<br></td></tr>
<tr><td>Background of the Proposal<br><br>sLmse=0.9825 NCC=0.7346<br>Mssim=0.9993 SI=0.9914**<br>PSNR= 17.5746</td><td>Background of Method[21]<br><br>sLmse=0.9946 NCC=0.9705<br>Mssim=0.9998 SI=0.9695*<br>PSNR= 22.6585</td><td>Background of Method[5]<br><br>sLmse=0.9976 NCC=0.9714<br>Mssim=0.9999 SI=0.9773*<br>PSNR= 26.2050</td></tr>
<tr><td colspan="3">The bold number indicate the better performance for the proposal than the two methods in [21,5] where the higher SI values inform that the proposal preserves the structural information more accurately.</td></tr>
<tr><td>Reflection of the Proposal<br></td><td>Reflection of Method[21]<br></td><td>Reflection of Method[5]<br>Not available</td></tr>
<tr><td colspan="3">The proposal can recover adequate reflection layer with a bright color compared with method in [21] that look like darker.</td></tr>
<tr><td colspan="2">Mixture input<br></td><td>Ground truth<br></td></tr>
<tr><td>Background of the Proposal<br><br>sLmse=0.9673 NCC=0.7503*<br>Mssim=0.9987 SI=0.7972<br>PSNR= 14.8611</td><td>Background of Method[21]<br><br>sLmse=0.9712 NCC=0.7310*<br>Mssim=0.9989 SI=0.9999<br>PSNR= 15.4022</td><td>Background of Method[5]<br><br>sLmse=0.9681 NCC=0.7554<br>Mssim=0.9987 SI=0.9940<br>PSNR= 14.9622</td></tr>
<tr><td colspan="3">The bold number of NCC indicate a more properly performance for the proposal than the method in [21]</td></tr>
</table>

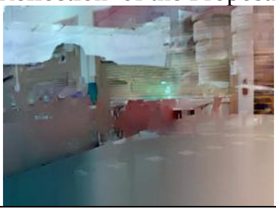
| Reflection of the Proposal | Reflection of Method[21] | Reflection of Method[5] |
|---|---|---|
|  |  | Not available |
| The proposal can recover adequate reflection layer with a clear reflection details and bright color compared with method in [21] that look like darker. | | |

**Figure 1:** quantitative and visual quality comparison results between the proposal and methods in [21,5] for wild scene dataset.

## Conclusion

This paper has proposed a simple and automatic algorithm to remove reflections from a single mixture image. The proposed algorithm classifies the reflection and background edges based on the fact that transmission edges are of larger magnitude than reflection edges using K-means clustering method that does not handle illumination cases correctly, therefore the proposed algorithm estimates specular reflections to separate reflection and background layer in a more accuracy. The experiments show acceptable performance, good results for remove specular reflection cases when compared with recent methods for both quantitative and visual qualities and the ability to remove reflections efficiently.

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