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Remove Reflections using Bisquare Iterative Reweighted Least Square

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Abstract
Reflections are ubiquitous effects in photos taken through transparent glass mediums, and represent a big problem in photography that impacts severely the performance of computer vision algorithms. Reflection removal is widely needed in daily lives with the prevalence of camera-equipped smart phones, and it is important, but it is a hard problem. This paper addresses the problem of reflection separation from two images taken from different viewpoints in front of a transparent glass medium, and proposes algorithm that exploits the natural image prior (gradient sparsity prior), and robust regression method to remove reflections. The proposed algorithm is tested on real world images, and the quantitative and visual quality comparisons were proved the better performance of the proposed algorithm on an average of 0.3% improvement on the **b**lind **r**eferenceless **i**mage **s**patial **qu**ality (brisque) error metric than state of art algorithm.

Keywords: Reflection removal, sparsity, superimposed image, motion, optimization.

ازالة الانعكاسات باستخدام طريقة اصغر المربعات التكرارية (Bisquare)

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الخلاصة
تعتبر الانعكاسات تأثيرات واسعة الانتشار في الصور التي يتم التقاطها من خلال وسط زجاجي شفاف, وتمثل هذه الانعكاسات مشكلة كبيرة في التصوير الفوتوغرافي وتؤثر بشدة على اداء خوارزميات معالجة الصور. ان استخدام كاميرات الاجهزة الذكية في التصوير بشكل يومي ادى الى زيادة الحاجة الى ازالة الانعكاسات والتي تعتبر مشكلة صعبة. هذا البحث يتناول مشكلة فصل الانعكاس من صورتين يتم التقاطهم بزاويتين مختلفتين من امام وسط زجاجي شفاف ويقترح استخدام طريقة اصغر المربعات التكرارية من نوع (Bisquare) في عملية الفصل والذي اثبت تفوقه في الاداء عن خوارزمية حديثة من خلال المقارنات الكمية والمرئية.

1. Introduction

Capturing photos through reflecting mediums using handheld smart devices such as smartphones and tablets under non optimal imaging conditions, leads to undesired reflections, and loss of information in the captured photos. These undesired reflections create ambiguity in image analysis applications and degrade the image quality. Therefore these images need to be pre-treated to remove reflection. The captured image through glass panes is a mixture of two sources, a background scene behind it, and a reflection of a scene on the same side of it, the goal is to keep the background scene and remove reflection information simultaneously [1]. Reflection removal is required as a preprocessing step in various image processing tasks that aims at separating the superimposition of the desired image, and the undesired reflections [2]. Reflection removal has been of much interest in

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recent years and to deal with this problem, hardware, manual post processing or multiple images are used to minimize the reflections effect. For instance, the polarizing lens is used by professional photographers to reduce, but not eliminate the reflections. Similarly, removing reflections using single mixture image is an underdetermined problem, and existing methods have to use prior knowledge to impose constraints to solve the problem, which has their specific limitations based on the nature of these priors. Therefore, using multiple images captured from different viewpoints makes the problem easier to work on that needs special requirements when capturing images [3].

The gradient domain image processing is defined as a type of digital image processing that operates on the differences between neighboring pixels, rather than on the pixel values directly. The processing of an image in the gradient domain produces subjectively better results than the conventional intensity domain processing, and the gradient domain method is basically matching the gradients with priors. Therefore, many recent image processing techniques operate in the gradient domain [4]. A robust property of natural images that has received much attention is the fact that when the derivative filter is applied to natural images, then the filter outputs tend to be sparse. The histogram of the output of a derivative filter is peaked at zero and falls off rapidly out to the two extreme ends of the histogram. This property can be formulated in a number of ways, e.g. in terms of their logarithm. The distribution of a natural image can often be modeled as a generalized Laplace distribution (generalized Gaussian distribution). Sparsity has been proved to be a powerful tool in several problems, and an important structure in image reconstruction techniques. Using prior information as regularization is a common practice for solving hard problems, which is a task dependent, and most natural images have sparse gradients which also called the natural image prior. [5]. Optimization means minimization or maximization of one or more functions with any possible constraints. One of popular classical optimization techniques is called Gradient method. The gradient optimization method uses knowledge of derivative information to locate optimum point [6].

The iterative reweighted least squares method (IRLS) is used to solve optimization problems; the sensitivity to the outliers is the main drawback of the least squares methods. Therefore, Bisquare Iterative Reweighted Least Square is used to minimize the outliers by assigning a low weight to them using an iteratively reweighted process. A bisquare weight is defined as the method that minimizes a weighted sum of squares, where the weight of each data point depends on its distance from the fitted line. The bisquare weights using an iteratively reweighted least squares method can be described in Eq. 1,2 and 3 as follows [7]:

$$W_i = \begin{cases} 1-(V_i)^2)^2 & |V_i| < 1 \\ 0 & |V_i| \geq 1 \end{cases} \quad \dots (1)$$

Where: $$V = \frac{R_{adj}}{K_s} \quad \dots (2)$$

$$R_{adj} = \frac{R_i}{\sqrt{1-H_i}} \quad \dots (3)$$

Where:

R_{adj} : the adjusted residuals.

R_i are the usual least squares residuals and H_i are leverages that adjust the residuals by reducing the weight of high leverage data points, which have a large effect on the least squares fit.

V:The standardized adjusted residuals.

K is a tuning constant equal to (4.685), and s is the robust variance given by (MAD/0.6745) where MAD is the median absolute deviation of the residuals.

This paper suggested removing the undesired reflections from two images of different viewpoints, which are taken through a transparent glass medium, and using the bisquare iterative reweighted least squares method for sparsity prior optimization in the separation stage. Experimental results showed better performance of the proposed algorithm than the state of the art method in the separation of background and reflection images.

2. Related Work

Remove reflection is still a challenging problem despite it has been studied for decades and required extra information to make the problem flexible, and to achieve any degree of success, the existing researches in reflection removal can be classified as single or multiple reflection removal methods. Single image reflection removal deals with a single mixture image that is a highly difficult problem compared with multiple image reflection removal, since trying to obtain two images reflection and background from just a single superimposed image, and a small number of aspirant methods try to solve it [8]. Some of these methods are used sparse gradient priors to classify the reflection and background edges as in [9, 10] that depend on user intervention to mark the reflection and, background image. Authors in [11] utilized values of gradient indirect manner, where separated images are reconstructed from the classified gradients that based on the smoothness constraint in the classification of gradients in the mixture image, as well in [12] that based on the gradient prior to separate the two layers by imposing a sparse gradient prior in the background image and, a smooth gradient prior on the reflection image, the work of [13] used the Depth Of Field (D.O.F) map to classify the edges to reflection and background. Most popular methods to remove reflections used multiple input mixture images under various conditions [14]. Authors in [15,16] have been proposed the motion computation for images captured from different viewpoints by using Scale Invariant Feature Transform flow (SIFT flow) to classify the edges as reflection or background edges in order to separate the reflection. Also, in [17] authors are used the correlation, and the sparsity of the gradient to separate reflection and background images from multiple images. The work of [18] used several images captured with different polarization angles, and based on a physical reflection model to estimate the reflection image. Similarly, in [19] a constraint on the disparity map is imposed that preserves the sharpness of the background image, and smoothing the reflection image, it utilized the truth that the reflections differ in multiple images taken from different viewpoints.

3. The Proposed Algorithm

This paper proposed an automatic reflection removal algorithm from two mixture images, which are captured from slightly different views in front of transparent glass mediums, that consisted of two stages detection and separation (remove reflection) as shown in Figure-1, where the mixture image pixels are automatically estimated and labelled as either reflection or background edges in the detection stage. And, in the separation stage the reflection and background images are reconstructed using the labelled reflection and background edges. The edge classification of the mixture image into either reflection or background is a key function of the detection stage, and it is very important to accurate the separation in the reflection removal process. Detection stage in the proposed algorithm has adopted the computation of intensity and motion values in [16] for each pixel to classify and label edges as either background or reflection. The intensity value corresponds to the pixel gradient magnitude value for the source image (Sim), therefore the work environment is the gradient domain, and then the motion vale between the source and target images is computed for every pixel to accurate edge classification, and obtain the detection of reflection and background images (RI, BI). This paper exploits the natural image prior (gradient sparsity prior) to reconstruct the reflection and background images in the separation stage using the labelled reflection and background edges RI, BI that obtained from detection stage. The proposed algorithm suggested the bisquare iterative reweighted least squares method used to optimize the sparsity prior. The sparse distributions are well modelled by a Laplacian distribution. For an image (I), the probability P (I_{BI}, I_{RI}) is tried to be maximized to separate the two images, which are equal to minimize the cost of (- log P (I_{BI}, I_{RI})). Based on the same inference in [10] and the following constraints:

- The input image I =IR+IB.
- The gradients of IR and IB agree with the gradients of the input image I at all locations.

The objective function is formulated as follows:

$$J\,(\mathrm{IB}) = \sum_{i,k} P(f_{i,k}\,.\,\mathrm{IB}) + P\Big(f_{i,k}.\,(\mathrm{I}-\mathrm{IB})\Big) + \gamma \sum_{i\,\epsilon\,\mathrm{BI},k} P\big(f_{i,k}\,.\,\mathrm{IB} - f_{i,k}.\,\mathrm{I}\big) + \gamma \sum_{i\,\epsilon\,\mathrm{BI},k} P\big(f_{i,k}\,.\,\mathrm{IB}\big) \qquad \ldots(4)$$

Where $f_{i,k}$ denotes the k_th derivative filters, first and second order derivative filters, and two orientations are used. The first term in the objective function keeps the gradients of the two layers as sparse as possible; the last two terms enforce the agreement with the detected gradients. This equation can be rewritten as in Eq.5 :

$$J\,(v) = \|Av - b\|_1 \qquad \ldots (5)$$

That minimized using bisquare iterative reweighted least square. Algorithm 1 describes the proposed stages to remove reflections from two mixture images.

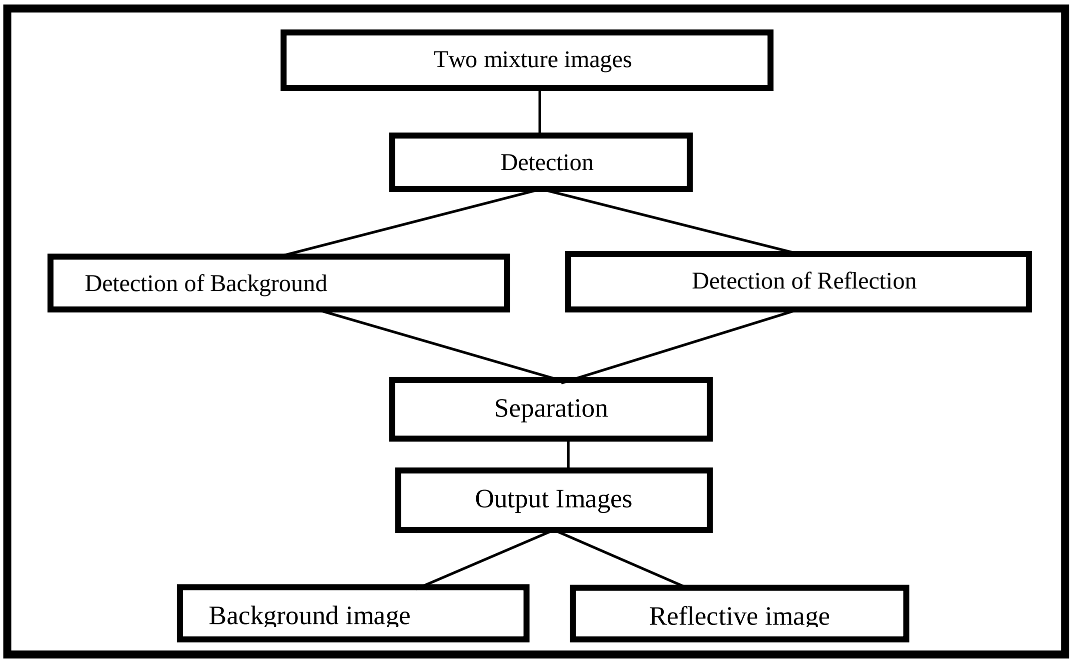

Figure 1-General scheme for reflection removal Algorithm

Algorithm 1: Remove reflections from two mixture images

Input: input source image Sim, target image Tim;

Output: I1,I2 background and reflection images;

Start
Initialization: itr $\longleftarrow$ number of iterations;
Step1: BI, RI $\longleftarrow$ detection of background and reflection edges using SIFT flow in [16] ; // Detection stage
Step2: A $\longleftarrow$ GX, GXX, GY, GYY; // first and second order derivative filters for two orientations.
Step3: For n=1 to 3 **do** ; // corresponding to (R,G,B) channels of Sim source image.
Step4: b $\longleftarrow$ A*Sim; // compute input source image derivatives.
X $\longleftarrow$ $(A^T*A)^{-1}*A^T*b$;
Step5: For m=1 to itr **do** ; // the value of itr is set to (3) empirically
er $\longleftarrow$ AX-b; // er: error or residuals.
ed $\longleftarrow$ er/sqrt(1-0.001); //compute the adjusted residual or error.
u $\longleftarrow$ ed / (8.685 * 0.9745); // standardize the adjusted residuals.
if |u| >=1 **then** // Compute the robust weights.
wg $\longleftarrow$ 0 ;
else
wg $\longleftarrow$ $(1-(u)^2)^2$;
end if
X $\longleftarrow$ $(A^T*wg*A)^{-1}*A^T*wg*b$
end for m
Step 7: I1(n) $\longleftarrow$ X; // I1 background image.
Step 8: I2(n) $\longleftarrow$ I- I1(n); // I2 reflection image .
end for n
end

4. Results

In this section, the effectiveness of the proposed algorithm is proved using real world images, the quality of background, and reflection images resulted from the proposed was tested by quantitative and visual quality comparisons to evaluate the performance of this work. The quantitative evaluation results were performed using brisque error metric, due to the lack of a dataset, or ground truth for two images reflection removal techniques. The brisque is a blind referenceless image spatial quality evaluator, and used when no reference, or ground truth image is provided. The value of brisque has ranged between 0 -100, where 0 value represented the best quality and 100 the worst [20]. The experimental results comparison between the proposed and method in [16] is shown in Figures-(2, 3). In terms of quantitative evaluation, the results in Figures-(2, 3) prove the outperformance of the proposed algorithm than method in [16] that provides a good separation of the background and reflection images as explained from the metric values that displayed below the background and reflection images, where the bold numbers indicate the better performance for the proposed. Four examples of visual quality comparison with method in [16] are shown in Figures-(2,3), it is evident that the proposed can remove most of the reflections that are framed in red, provide adequate reflection image and keep colors unchanged than method in [16] as shown in the two examples of Figure-2. Also, one can observe from Figure-3 the results of the proposed algorithm are better than results of method in [16], where the background and reflection images have no changed in color, most of the reflections are removed and the general details are shown clearly.

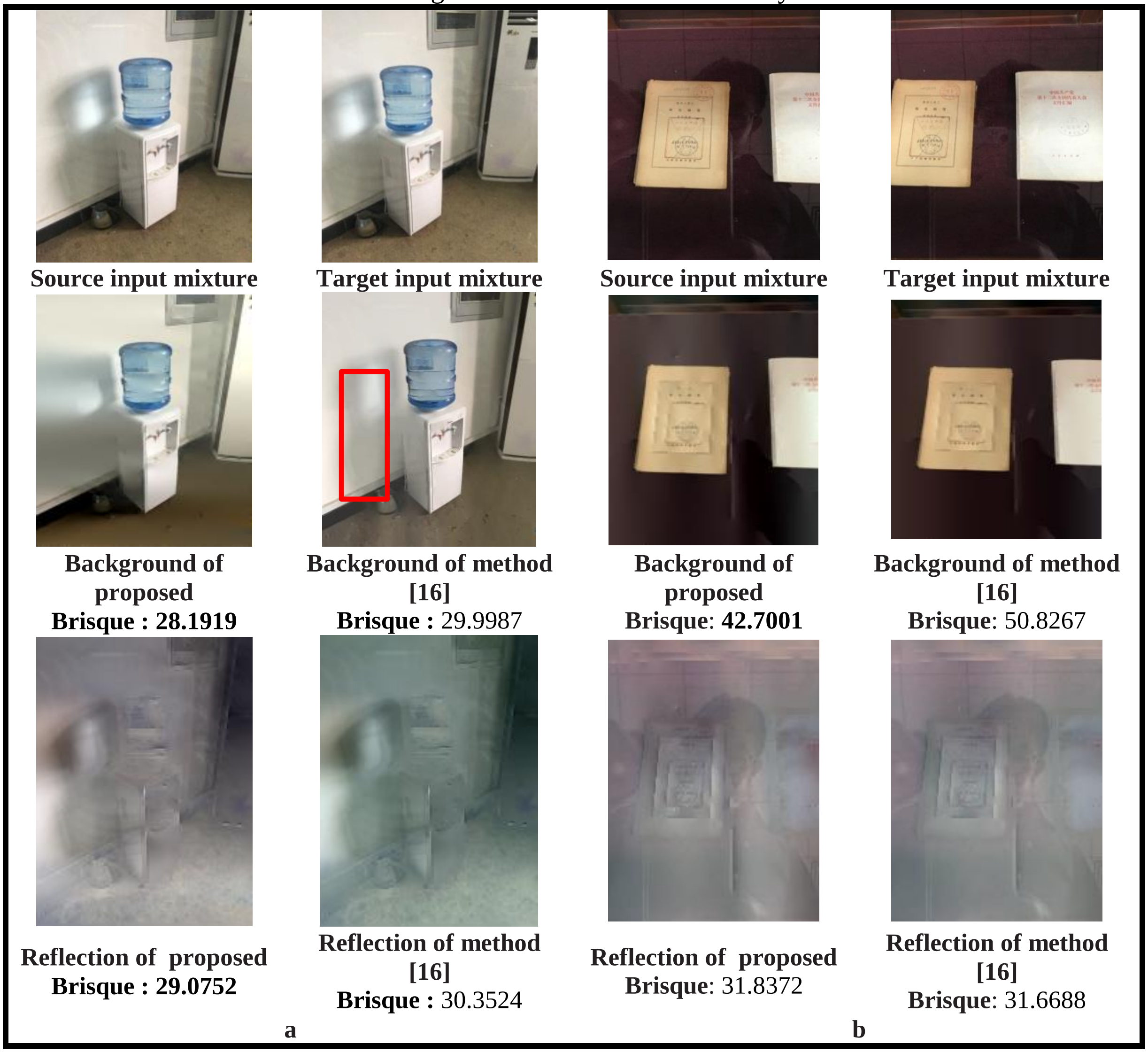

Figure 3-quantitative and visual quality results in comparison with methods in [16]

5. Conclusion

This paper has proposed an automatic reflection removal algorithm to separate reflections from two mixture images that extract background, and reflection images using gradient sparsity prior of natural images and bisquare iterative reweighted least squares method for optimization. The performance of the proposed has tested using real world mixture images and evaluated by quantitative and visual quality comparisons that proved the outperformance of the proposed than recent work and showed its ability to separate reflections efficiently.

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