Separating Reflections from Images Using Polarization Based Approach Includes Image Smoothening

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Abstract

When we take a picture through transparent glass, the image we obtain is often a linear superposition of two images: The image of the scene beyond the glass plus the image of the scene reflected by the glass. In this paper, we deal with a problem of separating the effect of reflection from such images captured behind glass. The input consists of multiple polarized images captured from the same view point but with different polarizer angles. The output is the high quality separation of the reflection layer and the background layer from the images without any prior knowledge about the images. We formulate this problem as a constrained optimization problem and propose a framework that allows us to fully exploit the mutually exclusive image gradients in each of the filtered images to achieve high quality reflection separation results. We test our approach on various images and found that our approach can generate good reflection separation results than the existing methods.

Keywords: *Gaussian Pyramid, Reflection Guide Map, Background and Reflection Mask Image.*

1. Introduction

The issue of reflection separation arises naturally in our everyday life when a desired scene contains another scene reflected off a transparent or semi-reflective medium. Common examples include photographs of scenes taken through windows or photographs of objects which are placed inside glass showcases found in retail store and museum settings. Reflections and transparency are about as ubiquitous as images themselves. Many natural images will typically contain one or both, i.e., contain mixtures of reflected and transmitted light. For example, any shiny or glass-like surface will create a reflected image of other surfaces in its immediate environment. Also, surfaces like glass and water are (at least partially) transparent, and hence will transmit the light from the surfaces behind it. Thus, many natural images are composed of reflected and transmitted images which are super-imposed on each other.

As digital photography becomes more pervasive, there are increasing efforts that aim at solving this problem through post processing instead of simply discarding corrupted images with reflection. By separating the contribution of reflection, one can refine a captured image to better see the desired scene. The image with reflection can be described by a linear superposition of two layers: the background layer from the scene beyond the glass and the reflection layer from the scene reflected by the glass. Decomposing the degraded input image into two layers is an ill-posed problem since there are an infinite number of ways to decompose an image. Fortunately, the reflection layer is a polarized image [Ref 1]. A common practice to reduce the effect of reflection is to place a polarizer in front of the camera lens to filter out the polarized light coming from reflection. However, the amount of polarization depends on the angle of incident light. In most cases, the reflected light is only partially polarized. Consequently, the reduced reflection layer may still remain in the filtered image. It is also common that when we change the rotation angle of the polarizer, reflection is reduced in certain parts of the image but remains in other parts.

We propose a method that uses multiple images filtered by a polarizer with different rotation angles for reflection separation. Our approach exploits the mutually exclusive image gradients in each of the filtered images to achieve high quality reflection separation results. We perform the operation of reflection separation by exploiting the effect of reflection under different rotation angles of a polarizer. Our study shows that for planar surface reflection, the region where the contribution of reflection is reduced to the maximum extent varies smoothly across an image as we slowly rotate the angle of the polarizer. Since the effect of reflection is additive, we would obtain a clear background layer with no reflection in an ideal case by combining the minimum intensity pixels of the filtered images [Ref 2].

However, since the reflected light is only partially polarized, weak reflection still remains in the background layer. We therefore use a better algorithmic approach on top of the polarizer for reflection separation. To accomplish our goal, we make a simple assumption that the image gradients of the background layer and the reflection layer are mutually exclusive [Ref 3]. Under this assumption, we can classify the image gradients into background layer gradients and reflection layer gradients using the information from the multiple input images. We formulate this reflection separation problem as a constrained optimization problem where the reflection layer, the background layer and the "matte" that determines the mixing coefficients of the reflection layer to each of the input images are solved iteratively.

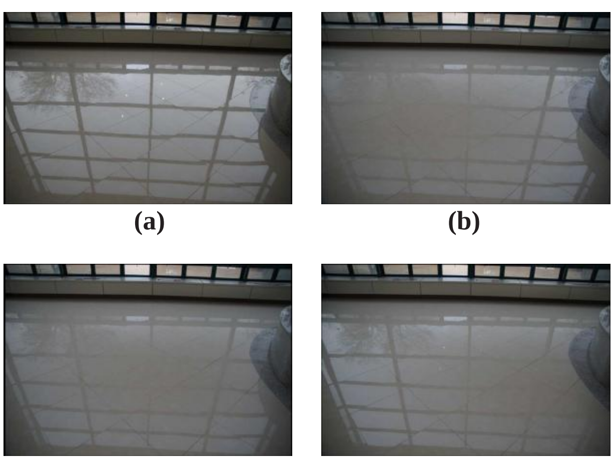

Fig.1. (a) Image captured without a polarizer, (b)-(d) Images captured with a polarizer rotated at different angles. The polarizer can reduce the reflection, but it cannot completely remove the reflection. Note that the reduced reflection depends on the rotation angle of the polarizer and it is spatially varying. [Ref 8]

2. Literature Survey

We categorized our surveyed papers as polarization and non-polarization based approaches.

2.1 Polarization Based Approaches

2.1.1 Separating Real and Virtual Objects from their Overlapping Images

Early work of the polarization-based approaches explored the reflection separation problem by simply collecting polarized pixel values. Ohnishi et al. [Ref 2] proposed to use the minimum intensity image over different polarizer angles as the background layer, and the image difference between the maximum intensity image and the minimum intensity image as the reflection layer. However, simply using a polarizer cannot fully separate reflection with partial polarization, and weak reflection may still remain in their recovered background image. The remaining reflection can be further reduced by analyzing the polarized images.

2.1.2 Polarization Based Decor-relation of Transparent Layers The inclination Angle of an Invisible Surface

Schechner [Ref 4] separated reflection based on physical analysis of polarization. Their method assumed some prior knowledge about the scene, such as an angle of incidence and a pair of polarizer angles that maximize and minimize reflection, which are hard to be measured directly in general.

2.1.3 Separating Reflections from Images Using Independent Component Analysis

Farid and Andelson [Ref 5] presented a method based on independent component analysis (ICA), which can separate reflection from two polarized images without using such prior knowledge. This paper describes how the statistical tool of independent components analysis can be used to separate some of these incidental components.

2.1.4 Sparse ICA for blind separation of transmitted and reflected images

Bronstein [Ref 6] generalized the ICA approach to allow multiple polarized images, while improving its accuracy and efficiency based on sparsity of large image gradients.

All of these approaches assume the contribution of reflection in each of the source images is spatially invariant, which is rarely satisfied for a real polarized image. On the other hand, our approach uses an alpha matte to model the spatially varying mixing coefficients of reflection for a polarized image, which is more physically accurate. This allows us to achieve reflection separation robustly without any physically-based prior knowledge about the objects in the scene.

2.2 Non- Polarization Based Approaches

2.2.1 User assisted separation of reflections from a single image using a sparsity prior

This method also employs a constrained optimization method with a single image as input data .Levin and Weiss [Ref 3] incorporated user input into the sparsity prior of image gradients to separate reflection from a single image. Their method used a dense set of user provided gradients, where each gradient was coupled with the reflection or background layer. In this approach, it would be very hard and labor-intensive to manually label dense gradients over such an input image.

2.2.2 Separating reflections from a single image using local features

Levin [Ref 7] simultaneously proposed an automatic method to find the most-likely decomposition which minimizes the total number of edges and corners in the recovered layers by using a database of natural images. However, these approaches may not work well if an input image contains complex structures or textures, namely many intersections of edges from the reflection and background layers. This approach is very slow, and candidate decompositions found by their database search may not include the desired decomposition. On the other hand, our method can work well even for the scenes containing such complex structures or textures, by automatically classifying the gradients from multiple polarized images with selective user correction.

3. Observations from Reflection Properties

A simple observation is that the amount of polarization depends on the angle of incidence. Such a partial polarization property explains that reflection separation by a polarizer cannot be perfect in practical situations since Brewster's angle (around 56∘ for glass reflection) is rarely set for image capture. Therefore, the polarizer cannot fully eliminate reflection at an angle of incidence away from Brewster's angle. We also note that the reflectance that determines the intensity of R also varies spatially within an image according to the angle of incidence. However, since our input images are all captured from the same view point, R is approximately the same across the images, and thus the variation of R over the images can be ignored. But this should not be ignored when we use "misalignment" information for reflection separation.

To estimate the mixing coefficients of reflection, we need to estimate the angle of incidence and the plane of incidence assuming that the refractive index of the reflection medium is available. However, it is difficult to directly measure such physical quantities from images without prior knowledge [Ref 4]. Such physical quantities could be indirectly estimated by incorporating them as unknown variables into an optimization formulation for reflection separation. However, this would make the optimization formulation overcomplicated.

To address these issues, we instead introduce a reflection model which is based on a smooth alpha matte assumption. The reflectance of each orthogonal component smoothly varies with respect to a continuous change of the angle of incidence. If we assume a pinhole-like camera and an almost planar glass surface, the angle of incidence spatially varies continuously and smoothly on the surface observed from the camera. We can conclude that both the reflected light off the surface and the transmitted light through the polarizer have spatially smooth variations on an image. Accordingly, the alpha matte should be smooth over the image. Using the alpha matte, we address the issue of partial polarization for robust reflection separation.

4. Module Descriptions and Assumptions

4.1 Construction of Gaussian Pyramid

The Gaussian pyramid consists of low-pass filtered, reduced density (i.e., down sampled) images of the preceding level of the pyramid, where the base level is defined as the original image. We adopt a multi-scale scheme based on a Gaussian pyramid with a scale factor equal to 2 in order to allow our reflection separation algorithm to converge to a solution close to the global minimum. Each input image $I_i(x)$ is down-sampled to construct the Gaussian image pyramid. At each scale, the mask image and reflection guide map are built. This image is used as the base for the preceding operations.

For each input image, we model the effect of reflection by the following equation for each of three color channels:

$$I_i(x) = \alpha_i(x)\, R(x) + B(x),$$

where I_i, R and B are the input image, reflection layer and background layer, respectively, x is pixel coordinates, i is an image index and α_i is a matte that represents the amount of reflection remaining in each of the polarized input images.

Our first assumption is that the gradients of the reflection layer and those of the background layer are mutually exclusive. In other words, if the magnitude of a gradient in an input image is larger than some threshold, such gradient can only come from either the reflection layer or the background layer, but not both. Our second assumption is that spatial variation of α_i within an image is smooth, that is, $\nabla\alpha_i(x) = 0$. This assumption comes from the fact that we are targeting at planar (smooth) surface reflection for which varies smoothly with the variation of the angle of incidence and other physical quantities.

4.2 Compute Reflection guide map and the Mask image

The following formula is used for calculating the reflection guide map,

$$\nabla I_i(x) = R(x)\,\nabla\alpha_i(x) + \alpha_i(x)\,\nabla R(x) + \nabla B(x),$$

where $\nabla = (\partial/\partial x, \partial/\partial y)^T$ is the gradient operator.

Under our assumptions, we can re-write this equation as follows:

$$\nabla I_i(x) = \alpha_i(x)\,\nabla R(x) \text{ or } \nabla B(x), \text{ if } \max_j|\nabla I_j(x)| \geq t$$

$$\alpha_i(x)\,\nabla R(x) + \nabla B(x), \text{ otherwise}$$

where $\max_j|\nabla I_j(x)|$ is the maximum magnitude of the gradient among all $\nabla I_i(x)$ and t is the threshold for image gradients in the first assumption. The threshold is determined by selecting the top two percentage of pixels which have the largest gradient magnitudes among all pixels in the input images. Note that according to this Equation, the contribution of $\nabla B(x)$ to $\nabla I_i(x)$ is fixed for all input images, while that of $\nabla R(x)$ varies depending on the values of $\alpha_i(x)$. Hence, if the variance of $\nabla I_i(x)$ over the input images is large, it is likely that the gradient $\nabla I_i(x)$ is from the reflection layer. Similarly, if the variance of $\nabla I_i(x)$ over the input images is small, it is likely that the gradient $\nabla I_i(x)$ is from the background layer. Therefore, the large gradient pixels, that is, the pixels with $\max_j|\nabla I_j(x)| \geq t$ can be classified into two layers, depending on their gradient variances over the images.

We construct a mask image M(x) which identifies the pixels with large gradients: $M(x) = 1$ if $\max_j|\nabla I_j(x)| \geq t$, and $M(x) = 0$ otherwise. The mask image consists of two parts, $M_R(x)$ and $M_B(x)$, which indicates the large gradient pixels from the reflection layer and the background layer, respectively. We set $M_R(x) = 1$ if $M(x) = 1$ and the pixel x has a large gradient variance over the input images, and $M_R(x) = 0$ otherwise. Similarly, we set $M_B(x) = 1$ if $M(x) = 1$ and the pixel x has a small gradient variance over the input images, and $M_B(x) = 0$ otherwise.

Given the mask image M(x), we can compute $\alpha_i(x)$, $\nabla R(x)$ and $\nabla B(x)$ for each pixel x such that $M(x) = 1$. We first initialize the values of $\alpha_i(x)$, $\nabla R(x)$ and $\nabla B(x)$ to zeros. If $M_R(x) = 1$, then $\nabla I_i(x) = \alpha_i(x)\nabla R(x)$ since the gradient is from the reflection layer.

The resulting values of $\alpha_i(x)$, $\nabla R(x)$ and $\nabla B(x)$ are stored in the reflection guide map and referred to as $\alpha'i(x)$, $\nabla R'(x)$ and $\nabla B'(x)$. These values are used as the guiding information for optimization.

4.3 Optimization of Results

The optimization problem is solved alternatingly for different sets of unknowns. At each scale other than the coarsest, the solutions for $\alpha_i(x)$ at the previous scale are up-sampled together with R(x) and B(x). With $\alpha_i(x)$ as initial guesses, the same solution method is applied to the optimization problem at this scale. While moving down the pyramid, the weights λ_i, λ_R and λ_B for regularization are adjusted: Specifically, λ_i, λ_R and λ_B are spatially varying, and more weights are assigned to $\lambda_i(x)$, $\lambda_R(x)$ and $\lambda_B(x)$ as the values $\alpha_i(x)$, $\nabla R'(x)$ and $\nabla B'(x)$ in the guide map approach to values of $\alpha_i(x)$, $\nabla R(x)$ and $\nabla B(x)$, respectively, which have been up-sampled from the solutions at the previous scale [ref 8].

5. Algorithm

Input: I_1 to I_N
Output: α_1 to α_N, R, B
Construct the Gaussian image pyramid.
For each level, from coarse to fine, in the multi-scale pyramid, do:
Compute the mask image and the reflection guide map.
If the current scale is the coarsest scale,
Initialize α_i using Eq. (7).
else:
    Up-sample the results of α_i, R and B.
    Evaluate the regularization weights $\lambda_{\alpha i}$, λ_R and λ_B.
end if
For a fixed number of iterations do:
    Estimate (R, B) with α_i fixed.
    Estimate α_i with (R, B) fixed.
end for
end for

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6. Implementation

In this section we simulate this project with suitable polarized inputs.

6.1 Input Images

Here these images shown in the Fig.2 are polarized one. However weak reflections still remain in the background layer. To accomplish our goal, we make a simple assumption that the image gradients of the background layer and the reflection layer are mutually exclusive [Ref 4]. Under this assumption, we can classify the image gradients into background layer gradients and reflection layer gradients using the information from the multiple input images. We formulate this reflection separation problem as a constrained optimization problem where the reflection layer, the background layer and the "matte" that determines the mixing coefficients of the reflection layer to each of the input images are solved iteratively.

(a)

(b)

(c)

Fig 2: Input Polarized Images for automatic Reflection Separation.

6.2 Construction of Gaussian Pyramids

We adopt a multi-scale scheme based on a Gaussian pyramid with a scale factor equal to 2 or 3 in order to allow our reflection separation algorithm to converge to a solution close to the global minimum. Each input image Ii(x) is down-sampled to construct the Gaussian image pyramid. At each scale, the mask image and reflection guide map are built. This image is used as the base for the preceding operations.

Scale1

Scale 2

Scale 3

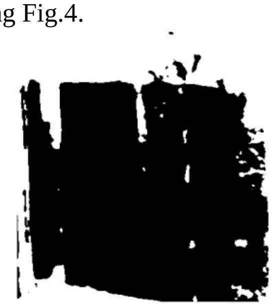
Fig.3: 3 levels of Gaussian Pyramid Construction

3 scale factor construction of Gaussian pyramid for input image. During the construction of Gaussian pyramids, the image gets blurred to option the global minimum.

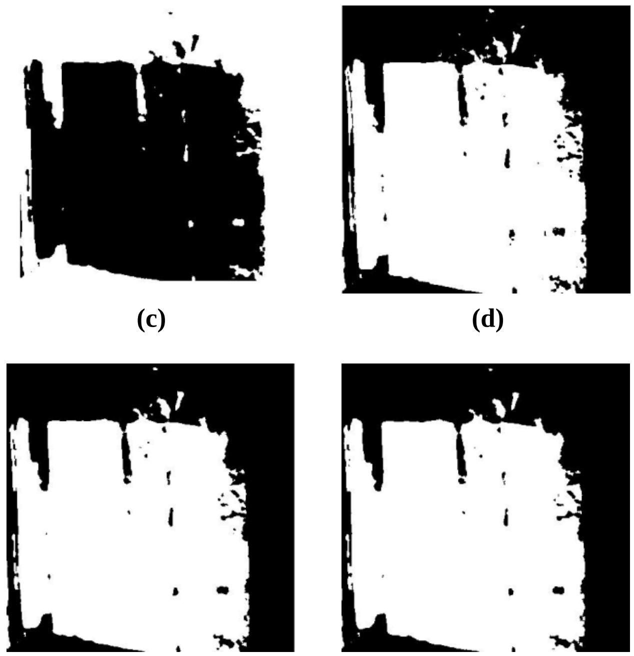
6.3 Computation of Mask Images

The mask images can be computed for each image using the formula mentioned in section (4.2). The generated mask images for background and reflection layers are shown in the following Fig.4.

(a)



(b)



(c) (d)

(e) (f)

Fig.4: (a)-(c) shows the mask images for background layer and Fig (d)-(f) shows the mask images for reflection layer.

Given the mask image M(x), we can compute $\alpha_i(x)$, $\nabla R(x)$ and $\nabla B(x)$ for each pixel x such that M(x) = 1. We first initialize the values of $\alpha_i(x)$, $\nabla R(x)$ and $\nabla B(x)$to zeros. If MR(x) = 1, then $\nabla I_i(x) = \alpha_i(x)\nabla R(x)$ since the gradient is from the reflection layer. In order to separate $\alpha_i(x)$ and $\nabla R(x)$ from $\nabla I_i(x)$, we set $\nabla R(x)$ to the gradient with the maximum magnitude over the input images. That is, $\nabla R(x) = \nabla I*(x)$ such that $|\nabla I*(x)| = \max_j|\nabla I_j(x)|$. For each input image $I_i(x)$, $\alpha_i(x)$ is obtained by projecting $\nabla I_i(x)$ onto $\nabla R(x)$: $\nabla I_i(x)\cdot\nabla R(x)$ $|\nabla R(x)|2$. If MB(x) = 1, then $\nabla I_i(x) = \nabla B(x)$. In this case, we set $\nabla B(x)$ to the gradient with $\max_j|\nabla I_j(x)|$.

6.4 Computation of Reflection Guide Map

The resulting values of $\alpha_i(x)$, $\nabla R(x)$ and $\nabla B(x)$ are stored in the reflection guide map and referred to as $\alpha'_i(x)$, $\nabla R'(x)$ and $\nabla B'(x)$. These values are used as the guiding information for optimization. Based upon the threshold value, the reflection guide map will vary. On average, three or four images of size about 350×350 were used as input data per experiment. Our optimization procedure takes about one minute to obtain an automatic solution.

After the reflection guide map computation, they are subjected to image smoothening and then the resultant background layer and reflection layer can be constructed using optimization process.

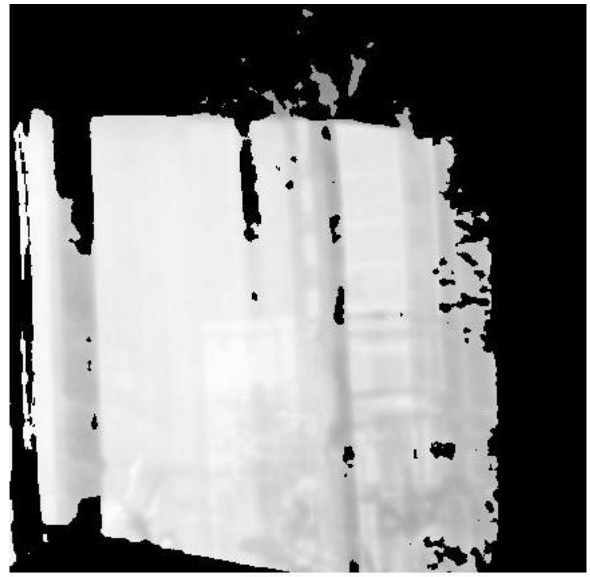


Fig.5 (a): Reflection Guide Map for Reflection Layer

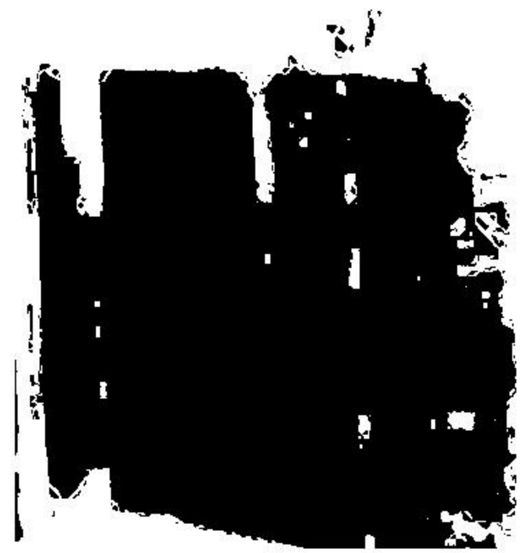


Fig.5 (b): Reflection Guide Map for Background Layer

7. Conclusions

In this work, we used an alpha matte to model the spatially varying mixing coefficients of reflection to separate the reflection layer and background layer separately from the polarized images based on some physical properties of reflections.

We also embedded the image smoothening process during the computation of reflection guide map. Through various experiments we made, we found that our automatic reflection separation mechanism produces the better results compared to other existing methods.

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