Detecting semi-specular reflection component from a sequence of images

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Abstract

In this paper, I address the problem of detecting incidental reflection from a sequence of images to improve the quality of background subtraction. This paper begins with a brief overview of previous work on separating specular-reflection from the reflective surface. The model I propose is based on a dichromatic illumination model, while not making any assumptions about the reflectance spectra and illumination change. The model is mostly using pixel information and some context information of images such as the color of foreground object in the scene. Unlike the previous methods, I attempt to retrieve the specular-reflection coefficient in the chromaticity color space to differentiate the specular-reflection component from the foreground component.

Following the explanation of the model, the results of the experiment can be found. I also offer some results from Linear Independent Component Analysis (ICA) and Blind Source Separation (BSS) for comparison's sake. The distribution of the specular-reflection coefficient shows that the linear discriminant function can be used in detecting the semi-specular reflection. This paper concludes with the significance of the model and poses the problems yet to be solved.

1. Introduction

Semi-specular reflection from a scene may cause destructive influence in background subtraction processes. For example, assume a person is standing up or is walking in front of a display window. Since the window has a reflective surface, the image of the person would be reflected in the shop window. If an image sensor detects the light reflected on the window, it may trigger a false alarm in a security and surveillance system. Just like the term "***Idolon specus***" has in it[1], the system tries to fight a shadow.

Though semi-specular reflection spreads the incident light a little bit, it still maintains the overall direction of the light and redirects the light by the angle of incidence.

1.1 Dichromatic Reflection Model [Shafer 85] [Wiemker 97] [Ragheb 01]

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[1] In **Novum Organum** by Sir Francis Bacon, an **idolon** (or **eidolon**) **specus** is a form of prejudice, by which someone inappropriately extends norms or tenets that apply to his own culture and social group, or to his own preferences(from wikipedia). **Idola** is interpreted as a species of illusion, or false appearance.

It describes the light *L*, which is reflected from a point on a dielectric and nonuniformal material, as a blend of the light L_{surf} reflected at the material surface (surface reflection) and the light L_{body} reflected from the material body (body reflection):

$$\mathbf{L = L_{surf} + L_{body}}$$

The light reflected on the surface ($\mathbf{L_{surf}}$) has approximately the same spectral distribution as the original light source. The light that is not reflected at the surface enters into the material body where it is scattered or selectively absorbed. Some fraction of the light arrives again at the surface and exits the material. The light traveling through the body is increasingly absorbed at wavelengths that are distinctive character for the material. The body reflection provides the characteristic color of an object.

1.2 Previous work on separating specular reflection

Since [Brelstaff 88] tried to detect specularity with Lambertian constraints, considerable progress has been made in the accuracy, the robustness and the flexibility of the separating methods. Intrinsic images are components of images that describe the scenes. Therefore, the observed image is a product of these components: an illumination image and a reflectance image [Weiss 01] (or specular and diffuse reflection components [Tan 03]). Separating these components from an image is known as a typical ill-posed problem because it has non-unique solutions.

This section gives some review of relevant work on the separation of reflective component from image(s).

1.2.1 Using a maximum a posteriori probability (MAP) – Bayesian framework

The recovery of surface orientation is the main concern of shape-from-shading. To get accurate surface normal geometry, [Ragheb 01] used MAP estimation method on a sequence of images. Using the surface normal information, they reconstructed the specular intensity component. Finally, they subtract the specular reflection from the original image intensity to get the Lambertian image.

This method could be a plausible solution to our problem in that the final goal is to label a pixel with Lambertian reflectance / specular reflectance mode, but the algorithm needs a consistent neighbor structure (computationally intensive and we have to maintain the probability models) that has notoriously poor global optimization properties.

1.2.2 Polarization based approach on a single view with constant / variable Fresnel ratio [Wolff 91] [Miya 03]

This method used polarization information of diffused light as well as specular light depending on the surface. By observing the light by a linear-polarizer-mounted camera, one can decide the polarization state of the light. The light intensity will vary when the polarizer is rotated. This intensity difference forms a sinusoidal curve with respect to the angle of the rotation of the polarizer. [Wolff 91] used this method to segment material surfaces based on the Fresnel reflectance model. If partial polarization measure were 0 then only the diffusion component would be captured (1 for pure specular component).

In [Miya 03], the texture was calculated from the diffuse only reflection component, after separating the reflection components of the images based on color. The illumination directions were determined from the position of the brightest intensity in the specular component. Finally, the surface roughness of the object was computed by using the estimated illumination distribution.

The framework adopted the Torrance-Sparrow model for the reflection model:

$$I = I_d + I_s,$$

where I is the observed intensity, I_d is the diffuse reflection intensity and I_s is the specular reflection intensity.

Like in our problem, they suffered from the fact that "extracting illumination intensity from reflection scale is an ill-posed problem". Consequently, they concentrated on deducing the reflection parameters from the polarized images assuming lots of other parameters in the light model are constant. This method also requires illumination chromaticity normalization, so that the illumination chromaticity needs to be known beforehand.

[Kim 02] did a similar approach to this method. They chose a color space decomposition method, divided the color space into the specular line space, and diffuse plane space. By using an appropriate energy function of line, they minimized specular variations.

One of the drawbacks this approach has is the incompleteness of the results. [Alexander 03] refers to some cases that the polarizer is not capable of removing the reflected component completely.

We can't use this method directly because our capturing devices are non-polarized cameras but some assumptions adopted here (linear combination of components, constant parameters) can be applied to my model.

1.2.3 Multiple views [Jin 02]

[Jin 02] sees the problem of estimating the shape and radiance of an object from a calibrated set of views (actually, they use a calibrated stereo rig) under the assumption that the reflectance of the object is non-Lambertian. Their approach is somewhat related to 1.2.5 in that it deals with stereo matching and reconstruction of images. Their model of photometry is based on the radiance tensor field, and they measured the discrepancy between model and images. In their model each pixel has more than 1 rank (Lambertian model has only one rank. "Diffuse + specular" reflection). By doing SVD and interpolation, they get the novel pixel information (this feature is similar to the method mentioned in 1.2.4)

[Lin 02] uses color analysis and multi-baseline (epipolar line) stereo to separate each component. By assuming Lambertian diffusion model (Viewpoint independent color), they tried to find stereo matching. Their model makes sense if the baseline of the camera is far away enough to get Lambertian diffusion at the other camera when they get specular reflection at one camera for the same pixel of the object (note that specular reflection is orientation sensitive). Nevertheless, their model doesn't fit to rough surface objects or mostly specular-reflective objects.

[Sato 96]'s solution consists of 3 steps. First, a sequence of images is measured by rotating a real object on a rotary table with fixed viewing and illumination directions. Secondly, components separation is done on the image pixel. Finally, they decide the parameters of Lambertian model and Torrance-Sparrow model.

The main goal of their work is get the consistent shape information regardless of intensity fluctuation caused by specular reflection. Therefore, the consistent image is enough for them rather than genuine pixel information with the correct depth information.

1.2.4 Using Image Signature [Weiss 01] [Tan 03a] [Tan 03b]

[Weiss 01] applied derivative filters on the set of images and calculate the ML reflectance function from the result of convolution. [Tan 03] used only one color image and make normalized image from it. While keeping the hue component of the image, they produced specular free image by shifting the intensity and chromaticity repeatedly. The assumption needed for their method is one-pixel diffusion, known illumination chromaticity and chromatic pixel (R≠G≠B) conditions. The reflection model is linear as follows:

$$\mathbf{I}(\mathbf{x}) = m_d(\mathbf{x})\mathbf{\Lambda}(\mathbf{x}) + m_s(\mathbf{x})\mathbf{\Gamma},$$

where the color vector of image intensity (**I(x)**) is decided by the weighted sum of diffuse reflection ($\mathbf{m_d(x)}$, diffuse reflection component), the weighted sum of specular reflection ($\mathbf{m_s(x)}$, specular reflection component), diffuse chromaticity (**Λ**) and illumination chromaticity (**Γ**).

Image transformation (DCT or wavelet – Haar - transformation) is frequently used in many computer vision problems from image compression to object recognition but I don't accept this idea because it needs local structure [Weiss 01] or computationally intensive operations even on one image [Tan 03].

1.2.5 Multi-layered component image concept [Szeliski 00] [Schechner 00a] [Schechner 00b]

The interpretation of image in this method is as follows:

"The projection of the scene on the image plane is multi-valued due to the superimposition of several contributions (Reflected and transmitted images [Szeliski 00])".

The semi-reflection of the object on the surface is called virtual object. Motion analysis, polarization and depth of field (DOF) are the main tools to gain information on the scene structure. [Schechner 00a] and [Schechner 00b] used polarized cue and [Szeliski 00] focused on motion recovery accuracy. Their work concentrated on only 2-layer structure and if the transparent layer doesn't contribute reflection, this method can't be applied.

In [Schechner 00a] and [Schechner 00b], depth cues do the crucial role for that removal of the inter-layer crosstalk (contamination). The assumptions they had are one layer of the image would be focused while the other is blurred and two superimposed images are independent to each other. Therefore, if we have stereo cameras to take images of the scene, the disparity between 2 different layers would be different. If the cameras were moving, motion parameters also would be far different. After separating two layers, they used a polarization cue to decide which one is a virtual / actual image.

In [Szeliski 00], they assumed when the camera is moving, the component layer images appear to move relative to each other. At each pixel, each layer partially attenuates the total amount of the light coming from all the layers behind it and adds its own light to give an output signal. Final composite image is the result of applying this process to all layers in a back to front fashion. The additive mixing ($\wedge$) of the images is:

$$F \wedge B \equiv F + (1 - \alpha_F) B$$

where F and B denote the colors of the foreground and the background images (we call $\wedge$ the *over* operator).

To recover the layers from the known motions they used the least squares technique and to estimate the non-dominant motion, Min-Max algorithm (Min for the motion estimation and Max for the difference detection) was used. This work primarily focused on the transparent layer – opaqueness makes the problem non-linear – in a homogeneous transformation.

Though [Schechner 00a]'s approach used 2 cameras instead of 1, [Schechner 00a], [Szeliski 00] all require quite global information to process ([Szeliski 00]'s method needed additional motion information).

I introduced the defocus blurred image idea and the notion of image composition as dynamics of a pixel feature to my framework.

1.2.6 Independent Component Analysis (ICA) [Farid 98] [Alexander 03]

This approach is based on a linear mixing process as the approaches above. According to their viewpoint, the image consists of a linear combination of the intrinsic (diffuse) component and the incidental (reflective) component, which can be separated by statistical tools. The reflection model of a pixel is:

$$y = aP + bR$$

where *a* and *b* are constants, and *P* and *R* are the amount of light contributed by an intrinsic surface point and a semi-reflected accidental object. The goal is the removal of the contribution of *R* from the equation above. One constraint for 4 unknowns makes the equation underconstrained (adding another equation only increases the number of unknowns). Let *Y* be a set of possible intensity values of a pixel (Mixed image intensity), *M* be a set of constant coefficients and *X* be a pair of contribution values (sources) of the surface and a reflected incidental object. Then:

$$Y = MX$$

What we want to know is the value of *X* ($M^{-1}Y$). To get *X*, they apply independent component analysis (ICA) with the assumptions of independence (source image level) and full-rank (Mixing matrix *M*). ICA is similar to the transformations such as singular vector decomposition (SVD) and principal components analysis (PCA).

The SICA approach [Alexander 03] is using Sparse ICA to separate superimposed images when we need the value of *X*.

However, requiring decorrelation between the estimated layers is based on the assumption that the original layers are decorrelated: that assumption is usually only an approximation [Schechner 00]. Moreover, the mixing matrix we have to deal with is singular, so one of the preconditions for ICA – full rank of M – can't be satisfied.

1.2.7 Psychophysically-based light reflection model [Ferwerda 2001]

In a traditional reflectance model, a color was described as an RGB triple and gloss was specified as ad-hoc model such as Phong's [Phong 75]. While the colorimetry has advanced toward more perceptually meaningful color spaces such as HSV, Munsell or CIELAB, light reflection models grounded in psychology failed to show much progress in surface gloss perception. [Ferwerda 2001] proposed a perceptual model through the following equations

$$\rho_d = f^{-1}(L)$$

$$\rho_s = \left(c + \sqrt[3]{f^{-1}(L)/2}\right)^3 - f^{-1}(L)/2$$

$$\alpha = 1 - d$$

where f is the normalized lightness function, L is the surface lightness; ρ_d is the object's diffuse reflectance, ρ_s - the energy of the specular component, **c** – the constant gloss, d – DOI (distinctiveness-of-image) gloss, and α – the spread of the specular lobe.

The model, however, is too constrained to the stimuli they gave. Therefore, a rigorous refinement of the model is required to prove that it can cover the space of physically plausible BRDF.

2. Separation methods for given constraints

In many ways, particularly for the reflection model, my model is analogous to that of [Tan 03b]. My framework, however, employs a model that can take information from background subtraction frameworks instead of chromaticity cues and deals with the reflection caused not by a light source but by other objects.

2.1 Reflection Model

I choose the dichromatic reflection model that states that the light reflected from an object is a linear combination of separable functions – diffuse and specular reflections. Therefore, each pixel of the image contains the information of diffuse and specular reflections.

$$I_c(x,y) = w_d(x,y) \int_\Omega S(\lambda) E(\lambda)\, q_c(\lambda)\, d\lambda + w_s(x,y) \int_\Omega E(\lambda)\, q_c(\lambda)\, d\lambda$$

where c = {R, G, B}, the type of sensors, $q_c(\lambda)$ is a vector of sensor sensitivity, w_d and w_s are the weight factors for diffuse and specular reflection respectively. $S(\lambda)$ is the diffuse reflectance function and $E(\lambda)$ is the spectral energy distribution function. Note that these functions are location independent. They only depend on the visible spectrum, Ω. The reflection model described above is the same as [Tan 03b]. If we assume the illumination isn't changed for a short period then the equation above can be simplified as follows:

$$I_c(x,y) = w_d(x,y)\, D + w_s(x,y)\, S$$

where D and S are interpreted as the amount of light contributed by the diffuse (Lambertian) reflection (D) and the specular reflection (S). The final equation resembles the image expression of [Farid 98].

The reasons I choose a dichromatic model over other models as a base of the reflection model are:

- It has fewer parameters to fix (Occam's razor).
- Its components are additive rather multiplicative.
- A lot of studies based on this model have produced, in some satisfactory degree, results.
- Saturation of color (originally white) seldom happens in the specular reflection.

Chromaticity used in my method is defined as follows (same as [Tan 03b]):

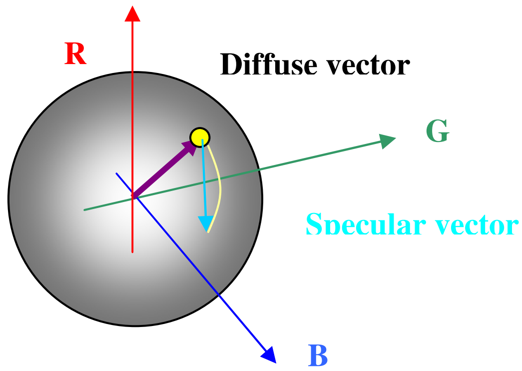
$$\sigma_c(x,y) = I_c(x,y) \;/\; \sum_{I = R,G,B} I_i(x,y),$$

where $\boldsymbol{\sigma_c}$ is the chromaticity and $\boldsymbol{I_c}$ is the image intensity.

2.2 Reflection component separation

In the rest of the paper, I assume that we have knowledge of the specular reflective areas. In order to discern the specular surface in a scene, we can apply all/any separation approaches referred to above (Section 1.2). Though the methods mentioned above are somewhat computationally intensive, detection of specular surfaces is only the one-time step operation. The premises I put into my model are 1) white light source, 2) convex specular surface (no inter-specular reflections) and 3) disregard of camouflage effect (The foreground object has a distinguishing chromaticity pattern compared to the background).

The basic idea of the model is based on the separable color space concept. Imagine a function that maps a pixel in the image to the 3-dimensional chromaticity vector space. Assuming the dichromatic reflection model, the square root of observed chromatic pixel value in a scene is the vector sum of constant diffuse reflection vector and variable specular reflection vector. Two constraints we have are 1) the distance from the origin is one and 2) specular reflection vector is pertaining to the chromaticity of the object that is reflected on the surface.



Consequently, the background pixel intensity can be expressed as:

$$I_c(x,y) = w_d(x,y)\, D + w_s(x,y)\, S$$

Solving the equation above is inherently ill-posed problem. Therefore, it requires assumptions on the photometric properties of the scene. This section describes the assumptions I put on my model. The value of c principally is c = {R, G, B} but I experimentally found the equation above could not hold if there is shadow cast on the surface. So from now on c means maximum chromaticity,

$$max(\ I_r(x,y),\ I_g(x,y),\ I_b(x,y)\ ) \,/\, \sum_{I\,=\,R,G,B} I_i(x,y)$$

2.2.1 Lambertian pixel assumption on the initial model of background

If an object reflected on the specular surface stands far away from the reflective surface, S converges to zero by the light source attenuation factor(f_{att} = min (1, 1/(c_1 + c_2d + c_3d^2))). This leads to diffuse-only reflection such as:

$$I_c(x,y)_{initial} = w_d(x,y)\, D$$

and will be modeled as a background.

When the specular reflection component due to a foreground object is presented in the scene, the pixel intensity would be changed into

$$I_c(x,y)_{crosstalk} = w_d(x,y)\, D + w_s(x,y)\, S = I_c(x,y)_{initial} + w_s(x,y)\, S$$

Therefore, the difference (offset) between the images is the specular component, $w_s(x,y)\ S$. My approach is different from [Farid 98]'s in that the final goal is to decide the coefficient $w_s(x,y)$, not the original image.

At one extreme, suppose the diffusion component is much greater than the specular reflection component ($w_d(x,y)\ D\ \gg w_s(x,y)\ S$). Then, hopefully the value of difference will be within underlying probability density function of background model. At the other extreme, if the specular reflection component dominates over the diffuse component ($w_d(x,y)\ D\ \ll\ w_s(x,y)\ S$), we can treat this case as full-specular reflection without blurring. The task I want to tackle lies somewhere between these two extreme cases. There is no clear-cut definition of semi-specularity. It may involve psychological factors as well as physical properties.

The simplest solution can be obtained when we have the information on the reflected image S from the scene. It is reasonable to expect that if the distance between the camera and the reflective surface is far enough, the object reflected on the surface also is captured in a scene (the radiation from the object should be strong enough to change the reflection pattern of the semi-specular reflective surface – this means the value of the light attenuation factor should be high). So the chromaticity value of adjacent foreground pixel serves as a good hint to estimate the value of $w_s(x,y)$. Once we get the value of $w_s(x,y)$ from a hint, we can appraise the range of semi-specular reflective pixel as follows:

$$I_c(x,y)_{initial} < \textit{Reflective pixel value} < I_c(x,y)_{initial} + w_s(x,y)\, S_{max}$$

The equation above implies trivially that if the reflective pixel value goes under $I_c(x,y)_{initial}$, we can label that pixel as a foreground pixel or shadow (each pixel gets darker). As long as the value of $w_s(x,y)$ is relatively small (<<1), the equation serves as good classification criterion.

What if we can't find any hint from a scene? On condition that the distance between the camera and the reflective surface is still significant, there are 2 factors that account for the specular reflection caused by an object: Very glossy surface and a very bright object. Very-glossy-surface hypothesis can be excluded by semi-specular assumption. On that account, we can set the value of $w_s(x,y)$ solely from S_{max}. Note that owing to the overestimation of S value (S_{max}), the coefficient $w_s(x,y)$ is somewhat underrated. Therefore, when we get the higher value for $w_s(x,y)$ during different time frames, we have to promote the value of that coefficient until it reaches the predefined maximum threshold. Defining the threshold value that can tell the specular reflection from foreground object is as difficult as determining semi-specular reflection.

2.2.2 Non-Lambertian pixel

Provided that the background pixel is already contaminated by the specular reflection, we can't apply the method mentioned in 2.2.1 for the reason that the equation "$I_c(x,y)_{initial} = w_d(x,y)\, D$" doesn't hold. The new equation of the background pixel is:

$$I_c(x,y)_{initial} = w_d(x,y)\, D + w_s(x,y)\, S_{initial}$$

Now the problem is extended to the general specular-reflection separation in section 2.1 (MAP, polarization camera, multiple views, image signature, multi-layer, ICA, SICA). Using the lowest intensity value (or maximum chromaticity intensity value) of the surface as an $I_c(x,y)_{initial}$ is not a bad idea on the condition that the specular-reflective surface has a uniform color-distribution. The rationale for selecting the lowest intensity pixel from the homogeneous surface can be found in [Tan 03b]. In [Tan 03b], they also selected the diffusion point from the chromaticity intensity space as in Figure 7.

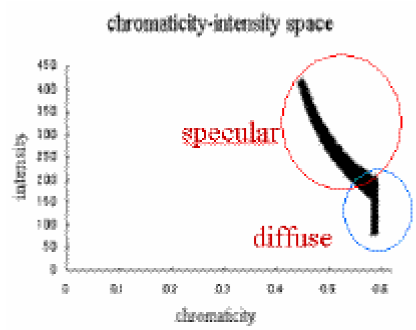


Figure 1. Chromaticity-intensity space. From [Tan 03a]

A canonical way to deal with this problem is to solve the equation.

$$I_c(x,y) = I_c(x,y)_{initial} + w_s(x,y)\, S - w_s(x,y)\, S_{initial}$$

$$I_c(x,y) - I_c(x,y)_{initial} = w_s(x,y)\,(S - S_{initial}) = offset$$

The offset is quite different from the previous one in section 2.2.1. If $S_{initial}$ is greater than S, the offset can be negative. Therefore the range of the chromaticity difference (S - $S_{initial}$) is from - S_{max} to S_{max} and we can compute the possible $w_s(x,y)$ value by applying two extreme values (-S_{max} for negative offset and S_{max} for positive offset). As mentioned in section 2.2.1, we need the promotion step on the set of possible $w_s(x,y)$ due to the overestimation of the chromaticity difference.

3. Experimental Results

The background model I used throughout the experiment is a single Gaussian Model for its simplicity and the capturing devices were Sharp CDC camera and Samsung C10-Web camera.

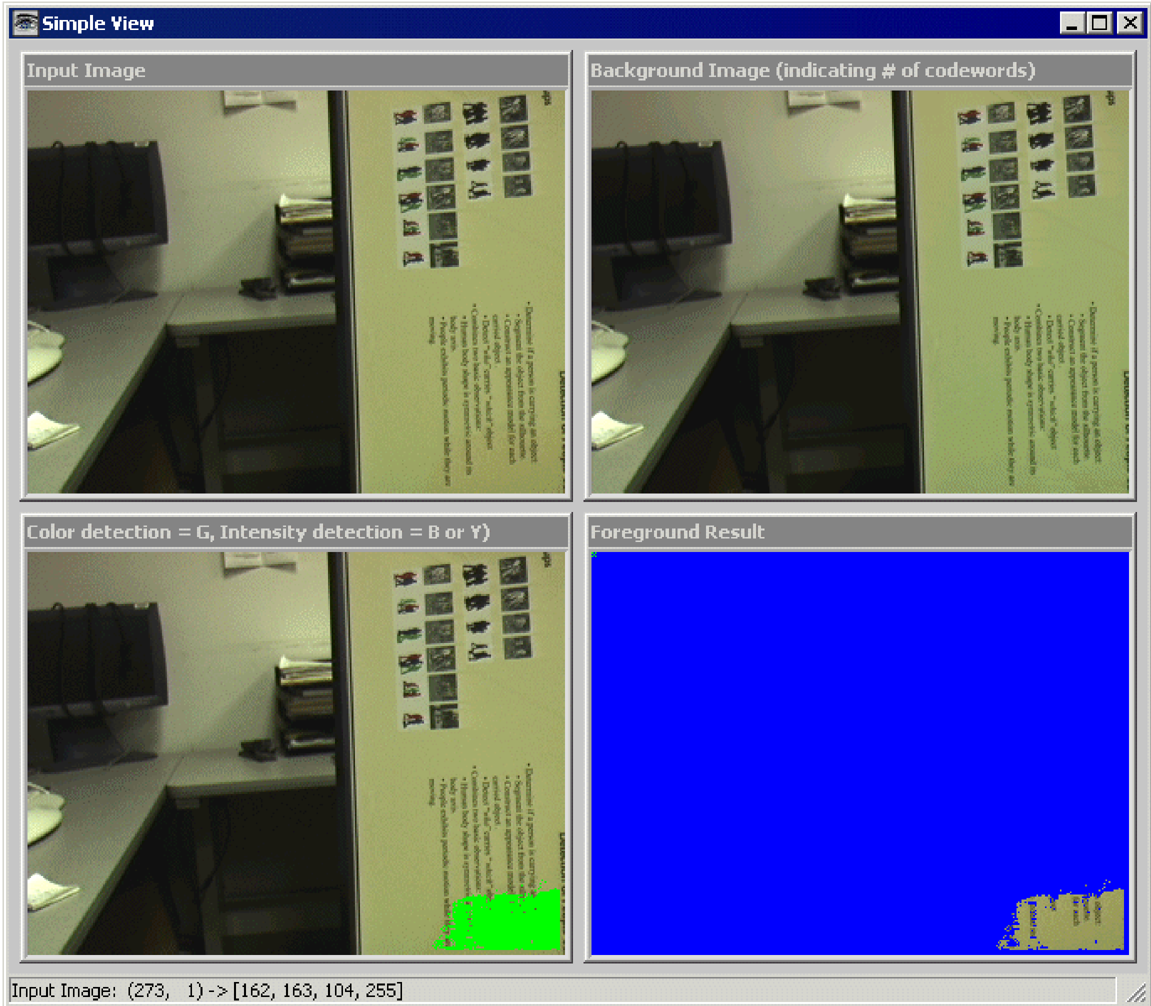


Figure 8- a. Background image (Upper right), input image (Upper Left) and non-background component (below)

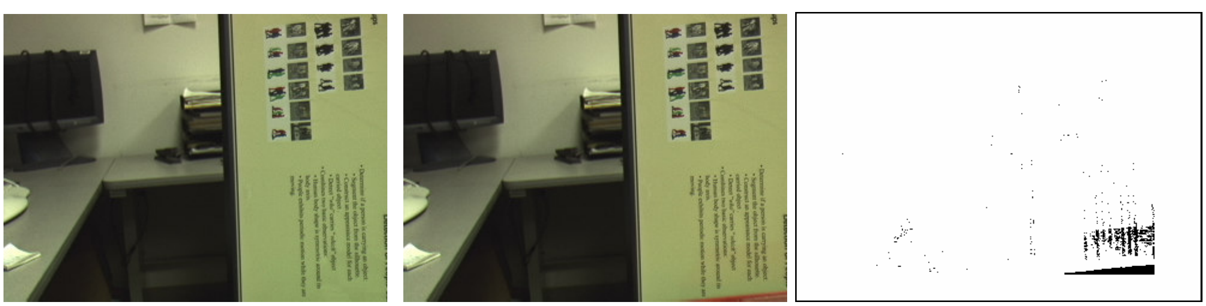


Figure 8-b. Background image (Left), input image (Center) and non-background component (Right)

Figure 8-a, and b. show the typical problem of specular reflection in background subtraction. The non-background components can have not only foreground components

but specular-reflection components. Moreover, the shape of specular-reflection is too poor to be useful.

3.1 Lambertian pixel assumption

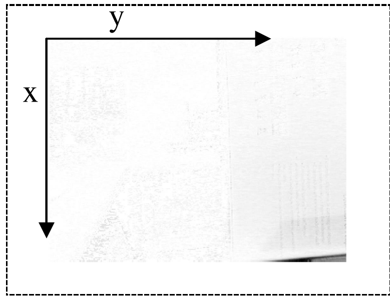


Figure 9. Reflective coefficient $w_s(x,y)$ distribution (red component) with known S.

Figure 9. clearly displays the difference of $w_s(x,y)$ coefficient between the foreground area and specular reflective area. The darker area represents the higher coefficient. It is interesting that the coefficient distribution reveals the shape information of the object reflected (this information can't be found from the raw image). This implies that if the reflectance surface is smooth and flat (such as a panel or a floor), the distribution of $w_s(x,y)$ is rather uniform. If we set the threshold value to 0.2, we can successfully separate two components (Figure 10).

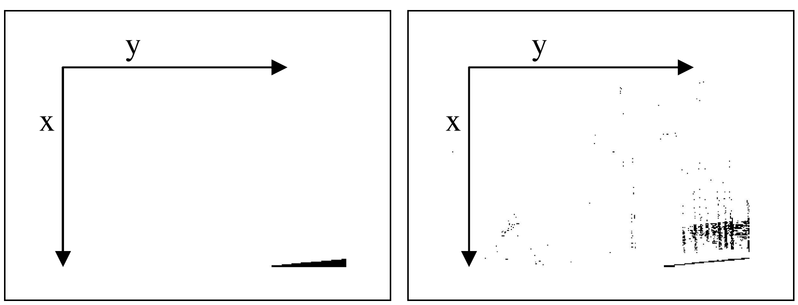


Figure 10. Results of separation. The foreground component (left) and reflection component (right) by the Red component.

If the foreground object comes into the image, that area has distinctive chromaticity distribution. Using this chromatic characteristic of color, we can separate the foreground component even without any hint on the object reflected on the surface (Figure 11) though we still have to identify the specular reflection.

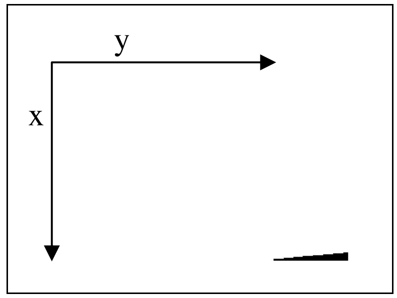


Figure 11. Separation of foreground solely by chromaticity change on the Green component.

Solving this problem without a hint (on the reflected object) produced the same results. Since we are dealing with the maximum chromaticity, the maximum ratio between the actual and the extreme chromaticity is theoretically 1: 3 and experimentally 1: 1.5. For the same reason, a non-Lambertian pixel also is classified correctly (The example above contains, though a small fraction, the reflected image initially. The results would be presented in 3.2).

Finally, if there is no hint on the reflected image, how can we conclude a color component as the maximum chromaticity? The method I used is to calculate the chromaticity differences on all 3 color components(R,G,B) and choose a component with the greatest difference.

3.2 Non-Lambertian pixel assumption

Imagine the shiny floor surface that reflects objects adjacent to it. The pixel of the floor surface has already had the specular reflectance component from the beginning and presumably this will make the separation step harder. On the contrary, the initial specular reflection component doesn't hinder from the separation of specular reflection (Figure 12, figure 13).

Figure 12. Background image (Left), input image (Center) and non-background component (Right)

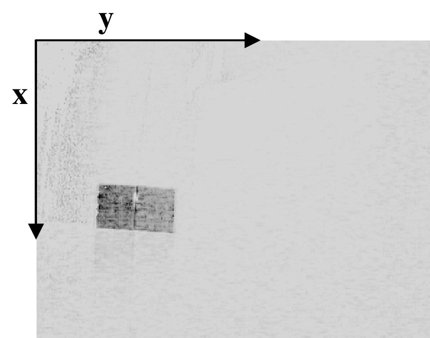


Figure 13. Reflective coefficient $w_s(x,y)$ distribution (red component) with unknown *S*.

Below is the result of specular-reflection detection with the threshold (the value of $w_s(x,y)$) of 1.2 (with hint, the threshold value goes up to 1.8). The mean of $w_s(x,y)$ on the specular reflection area is 0.03.

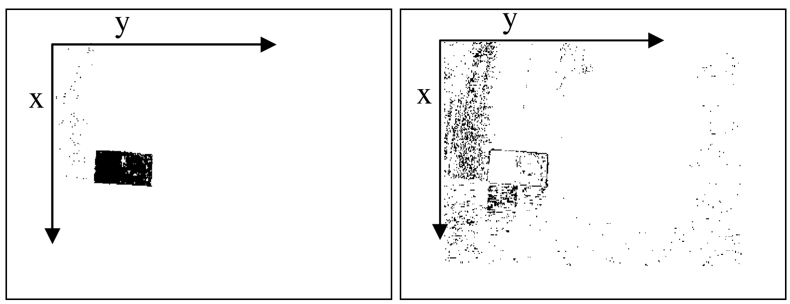


Figure 14. Results of separation. The foreground component (left) and reflection component (right) by the Red component.

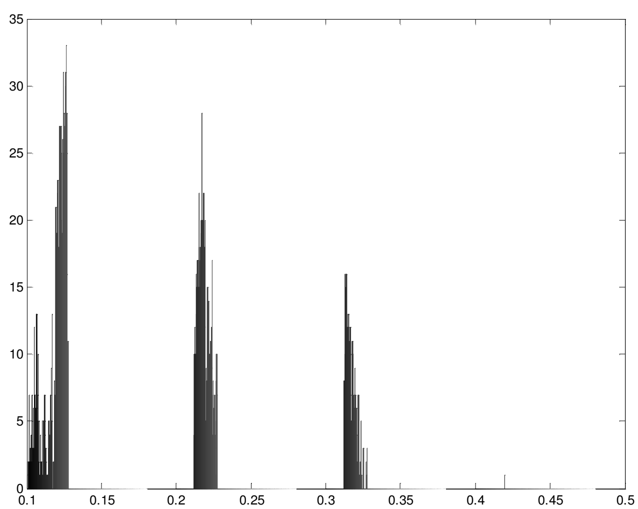


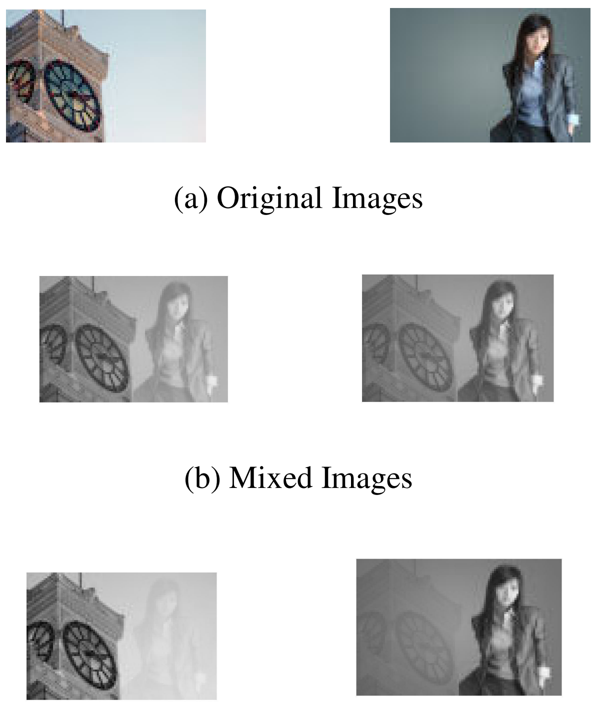
Figure 15. Histogram of Reflective coefficient $w_s(x,y)$ distribution (red component) with unknown *S*.

As shown in Figure 15, the coefficient value has linearly separable distribution that makes the threshold method valid.

3.3 Linear Independent Component Analysis (ICA) and Blind Source Separation (BSS) [Almeida 05]

One of the difficulties in applying ICA to the reflection detection is the mixture process. If you just change the intensity of the light, the mixing matrix goes singular. Taking pictures from different locations causes image alignment problems.

To avoid these problems for a feasibility study, I mixed the intensity of the pixels after capturing 2 different images. Figure 16 shows original images, mixed images and separated images respectively. The most critical problem I've faced was the incomplete removal of the reflected image (Figure16-(c)). Since the process of measuring nongaussianess in ICA is the process of approximation, the trace of the reflection still lingers after the separation process.



(a) Original Images

(b) Mixed Images

(c) Separated images

Figure 16. Original, mixed and separated images from ICA

4. Conclusion

I have proposed a method to detect the specular reflection component from a sequence of images. The striking difference of my model to the previous research is in that my model tries to find parameters of specular reflection instead of recovering the diffuse reflection.

The results of the experiment show that a foreground color component has higher $w_s(x,y)$ value (> 0.2) than that of specular-reflection component (<0.03). The hint on the reflected image (from the foreground information) is helpful to determine $max(I_r(x,y), I_g(x,y), I_b(x,y))$ when we calculate $w_s(x,y)$ but is of little use of deciding the threshold of $w_s(x,y)$ – but still a good guideline.

Because of shadow, I had to use chromaticity value instead of illumination intensity value. Therefore the dichromatic equation "$I_c(x,y) = w_d(x,y) D + w_s(x,y) S$" should be changed into a chromatic version. If you divide the previous equation by "$\sum_{I=R,G,B} I_i(x,y)$", the resultant becomes a non-linear equation. Intuitively, for the maximum chromaticity "$I_c(x,y) = w_d(x,y) D + w_s(x,y) S$" holds and $w_s(x,y)$ is directly proportional to the intensity of the color ($w_s(x,y) \propto \sum_{I=R,G,B} I_i(x,y)$ can be confirmed by the experimental result) but I can't find any rigorous justification on the linear combination of chromaticity yet.

A model for discovering a threshold value of $w_s(x,y)$ can be studied through psychological approach or statistical (linear discriminator) approach. In most of the cases, the range for the $w_s(x,y)$ value of the semi-specular reflection is 0.02 to 0.03. The proposed model needs a rigorous way of deciding a threshold without the information of foreground object.

The advantages of this approach over simple thresholding (for example, if the offset is greater than the background model and less than 5 per cent of background pixel value then label it as a specular-reflection pixel) are:

- By incorporating the foreground information in the model, it can detect the specular image on the highly reflective surface.

- This approach can reconstruct the shape and the color composition of the object reflected on the surface even if the scene doesn't contain the object (refer section 3.1).

- $w_s(x,y)$ gives the information of the specular-reflective surface. Therefore, we can segment the reflective surface by the value of $w_s(x, y)$.

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