Bayesian Reflectance Component Separation

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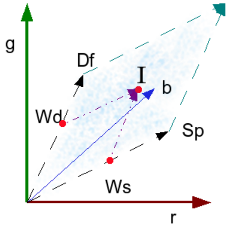
Introduction

- We work on a Bayesian approach to the estimation of the specular component of a color image, based on the Dichromatic Reflection Model.
- The separation of diffuse and specular components is important for color image segmentation.
- In this work we postulate a prior and likelihood energies that model the reflectance estimation process.
- Minimization of the posterior energy gives the desired reflectance estimation.
- The approach includes the illumination color normalization and the computation of a specular free image to test the pure diffuse reflection hypothesis.

Reflection Modelling



This sketch represent the Dichromatic Reflection Model (DRM). It was introducer by Safer

- The perception of a surface point can be expressed as the sum of two components
  - The first one represent the **diffuse component**. It has a direcction and a weigthing factor
  - The other one represent the **specular component**. It has a direcction and a weigthing factor too

Reflection Modelling

$$\mathbf{I}(x) = w_d(x) \int_{\Omega} S(\lambda, x) E(\lambda) \mathbf{q}(\lambda) d\lambda + w_s(x) \int_{\Omega} E(\lambda) \mathbf{q}(\lambda) d\lambda \tag{1}$$

$$I(x) = w_d(x)\mathbf{B}(x) + w_s(x)\mathbf{G}, \tag{2}$$

- $\mathbf{I} = \{I_r, I_g, I_b\}$ is the color of an image pixel obtained through a camera sensor
- $x = \{x, y\}$ are the two dimensional coordinates of the pixel in the image
- $\mathbf{q} = \{q_r, q_g, q_b\}$ is the three element vector of sensor sensitivity
- $w_d(x)$ and $w_s(x)$ are the weighting factors for diffuse and specular components, respectively
- $S(\lambda, x)$ is the diffuse spectral reflectance
- $E(\lambda)$ is the illumination spectral power distribution function
- The integration is done over the visible light spectrum Ω

Reflection Modelling. Chromatic Terms

Image Chromaticity (normalized RGB space)

$$\Psi(x) = \frac{\mathbf{I}(x)}{I_r(x) + I_g(x) + I_b(x)} \tag{3}$$

Diffuse Chromaticity

$$\Lambda(x) = \frac{\mathbf{B}(x)}{B_r(x) + B_g(x) + B_b(x)} \tag{4}$$

Specular or Illumination Source Chromaticity

$$\Gamma = \frac{\mathbf{G}}{G_r + G_g + G_b} \tag{5}$$

Reflection Modelling. Chromatic terms

Image written in terms of diffuse an specular chromaticity

$$I(x) = m_d(x)\Lambda(x) + m_s(x)\Gamma \quad (6)$$

The illumination normalized image is computed as

$$I'(x) = \frac{I(x)}{\Gamma^{est}(x)} \quad (7)$$

where Γ^{est} is the estimation of the illumination color.

The normalized image can be expressed as

$$I'(x) = m'_d(x)\Lambda'(x) + m'_s(x)/3 \quad (8)$$

where Λ' is the normalized diffuse chromaticity.

Reflection Modelling. Specular Free Image

$$I'(x) = m'_d(x)\Lambda'(x) + m'_s(x)/3$$

$$\tilde{I}(x) = min\{I'_r(x), I'_g(x), I'_b(x)\}$$

$$\tilde{\Lambda}(x) = min\{\Lambda'_r(x), \Lambda'_g(x), \Lambda'_b(x)\}$$

$$\tilde{I}(x) = m'_d(x)\tilde{\Lambda}(x) + \frac{m'_s(x)}{3} \quad (9)$$

Specular-Free

$$I^{sf}(x) = I'(x) - \tilde{I}(x) = m'_d(x)\left[\Lambda'(x) - \tilde{\Lambda}(x)\right] \quad (10)$$

Reflection Modelling. Separation Method

- Our goal is look for a diffuse image. That is, we are going to remove the specular component
- Then we are going to explore the mathetical properties of the Specular Free image
- We rely on the derivative of the logarithm to formulate an equation for the energy function of a bayesian model

Reflection Modelling. Separation Method

A diffuse pixel in a normalized image

$$I'(x) = m'_d(x)\Lambda'(x) + m'_s(x)/3$$

$$I'(x) = m'_d(x)\Lambda'(x)$$

$$I'(x) = m'_d(x)\Lambda'$$

$$log(I'(x)) = log(m'_d(x) + log(\Lambda'))$$

$$\frac{\partial}{\partial x} log(I'(x)) = \frac{\partial}{\partial x} log(m'_d(x))$$

A pixel in a Specular Free Image

$$I^{sf}(x) = m'_d(x)\Lambda^{sf}(x)$$

$$I^{sf}(x) = m'_d(x)\Lambda^{sf}$$

$$log(I^{sf}(x)) = log(m'_d(x) + log(\Lambda^{sf}))$$

$$\frac{\partial}{\partial x} log(I^{sf}(x)) = \frac{\partial}{\partial x} log(m'_d(x))$$

Reflection Modelling. Separation Method

The method is based on the difference of the image logarithm differentials

$$\triangle(x) = dlog(I'(x)) - dlog(I^{sf}(x)) \quad (11)$$

if $\triangle(x)$= 0, then is a diffuse pixel

With this strategy we can detect diffuse pixels.

Bayesian Modelling

Given an image f and a desired unknown response of a computational process d, Bayesian reasoning gives, as the estimate of d, the image wich maximizes the *A Posteriori* distribution

$$P(d|f) \propto e^{-U(d|f)}$$

where $P(d|f)$ is equivalent to $e^{-U(d|f)}$

Bayesian Modelling

- We assume a Gibbisian distribution for the potential energy.
- Besides the *A Posteriori* energy $U(d|f)$ can be decomposed in to the *A Priori* $U(d)$ and Likelihood (Conditional) $U(f|d)$ energies

$$U(d|f) = U(f|d) + U(d)$$

The Maximum A Posteriori (MAP) estimate is equivalent minimize the posterior energy function

$$d^* = \arg\min_d U(d|f) \tag{12}$$

Bayesian Modelling

A Posteriory Energy = A Priory Energy + Likelihood Energy

Likelihood

The **Likelihood energy** $U(f|d)$ measures the cost caused by the discrepancy between the input image f and the solution d.

Prior

The **A Priori energy** $U(d)$ is a model of the desired solution.

Bayesian Modelling. Likelihood Energy

We will assume a Gaussian Likelihood distribution plus a Chromaticity preservation constraint, therefore the Likelihood energy will have the following expression:

$$U(f|d) = \sum_{i=1}^{m} \frac{(f_i - d_i)^2}{2\sigma^2} + \sum_{i=1}^{m} \left(\Psi_i^f - \Psi_i^d\right)^2 \tag{13}$$

where f_i and d_i are the RGB pixel values a the i-th pixel position for the observed and desired image, respectively. Also, Ψ_i^f and Ψ_i^d denote the chromaticity pixels of the observed and desired image, respectively.

Bayesian Modelling. A Priori Energy

The A Priori energy is built up from two components.

$$U(d) = U_{\triangle}(d) + U_{\Psi}(d) \tag{14}$$

The first one models the Chromaticity continuity:

$$U_{\Psi}(d) = \sum_{i=1}^{m} \sum_{j \in N_i} \sum_{c \in \{r,g,b\}} \left(\Psi_{i,c}^{d} - \Psi_{j,c}^{d} \right)^2$$

This equation is necesary, because we are assuming that two neighboring pixels have the same chromaticity. It oblied us to detect and reject noise pixels and color discontinuity pixels

Bayesian Modelling. A Priori Energy

The second term models the estimation of the derivatives as the cliques of the RMF. That is, we assume that the local energy at pixel d_i is defined as

$$U_{\triangle}(d_i) = \left(dlog(d_i) - dlog(d_i^{sf}) \right)^2$$

where d_i^{sf} is the i-th specular free pixel.

Bayesian Modelling. A Priori Energy

- The second term of A Priori energy is derived as:

$$U_{\triangle}\left(d_i\right) = \left(\sum_{j\in N_i}\sum_{c\in\{r,g,b\}} \log \frac{d_{j,c}d_{i,c}^{sf}}{d_{i,c}d_{j,c}^{sf}}\right)^2$$

- The derivative component of the A Priori energy is, therefore, the addition of these local energies:

$$U_{\triangle}\left(d\right) = \sum_{i=1}^{m} U\left(d_i\right)$$

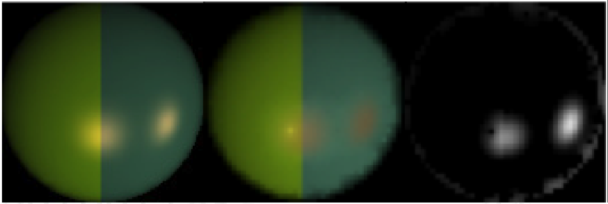
- And the A Priori energy is given by the addition.

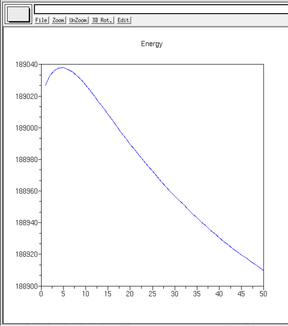
$$U\left(d\right) = U_{\triangle}\left(d\right) + U_{\Psi}\left(d\right) \qquad (15)$$

Experimental Results

- The starting value for the energy minimization process is set to $f = d(0) = \mathbf{I}'$.
- Each iteration step of the energy minization involves the computation of the specular free image $d^{sf}(t)$ of the current hypothesis $d(t)$ of the optimal estimation d^*.
- We have employed a simple heuristic to determine the new hypothesis $d(t+1)$, consisting in the reduction of the intensity of the pixels preserving their chromacity components relative ratios.

Experimental Results

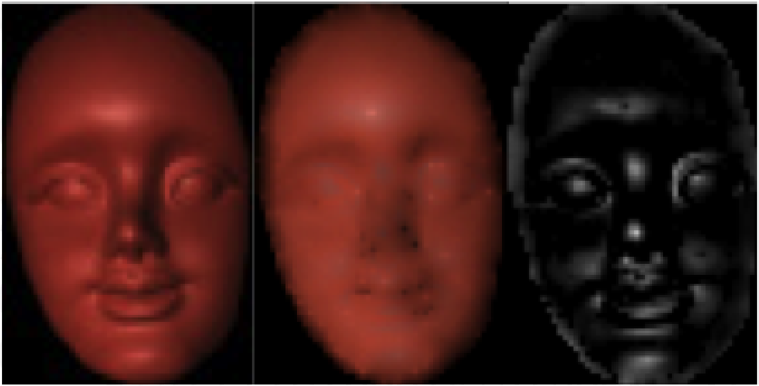




From left to right:

1. The original image
2. The estimated diffuse image
3. The estimated specular image
4. The energy behavoir

Experimental Results



From left to right:

1. The original image
2. The estimated diffuse image
3. The estimated specular image

Conclusions

- We have presented a Bayesian approach to the problem of reflection component separation
- Our approach needs only one image
- We compute the specular free image, which can be done on the fly for each hypothesis
- The problem of diverse color illumination sources will be dealt with in further works.


Thank You!