

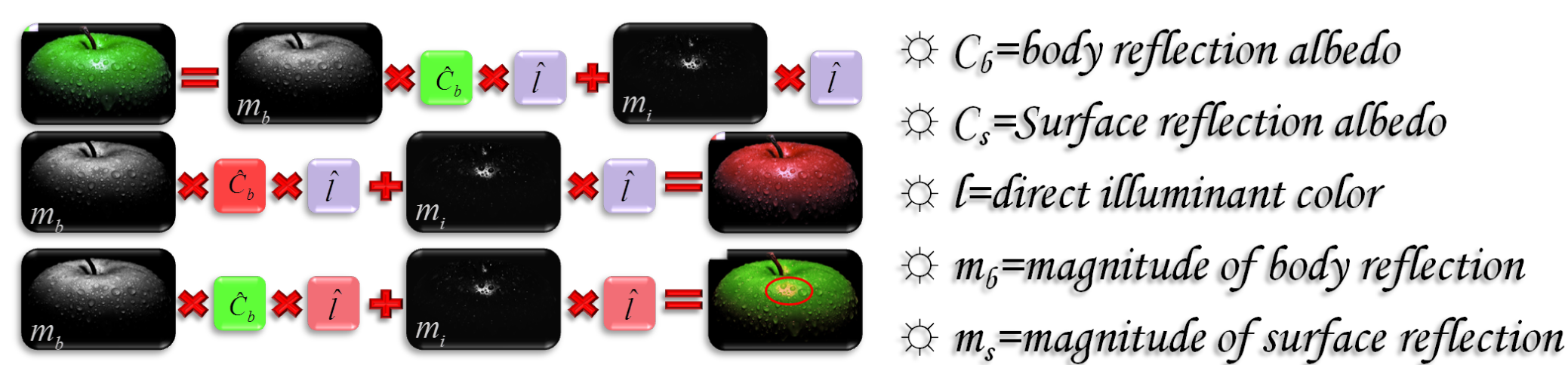
Abstract

Object recoloring is one of the most popular photo-editing tasks. Existing recoloring methods limit their application to diffuse objects or objects lit by a white illuminant. We perform realistic *recoloring* and *relighting* of single-colored objects lit by multiple colored illuminants in complex uncalibrated natural images. Further applications are: *enhanced photofusion* and *color transfer*.

DRM

The *Dichromatic Reflection Model*(DRM) [1] models the object reflectance. We assume *neutral interface reflectance*, therefore $c_s = 1$.

$$\mathbf{f} = m_b \mathbf{c}_b + m_s \mathbf{c}_s = m_b \mathbf{cL} + m_s \mathbf{l}, \quad (1)$$



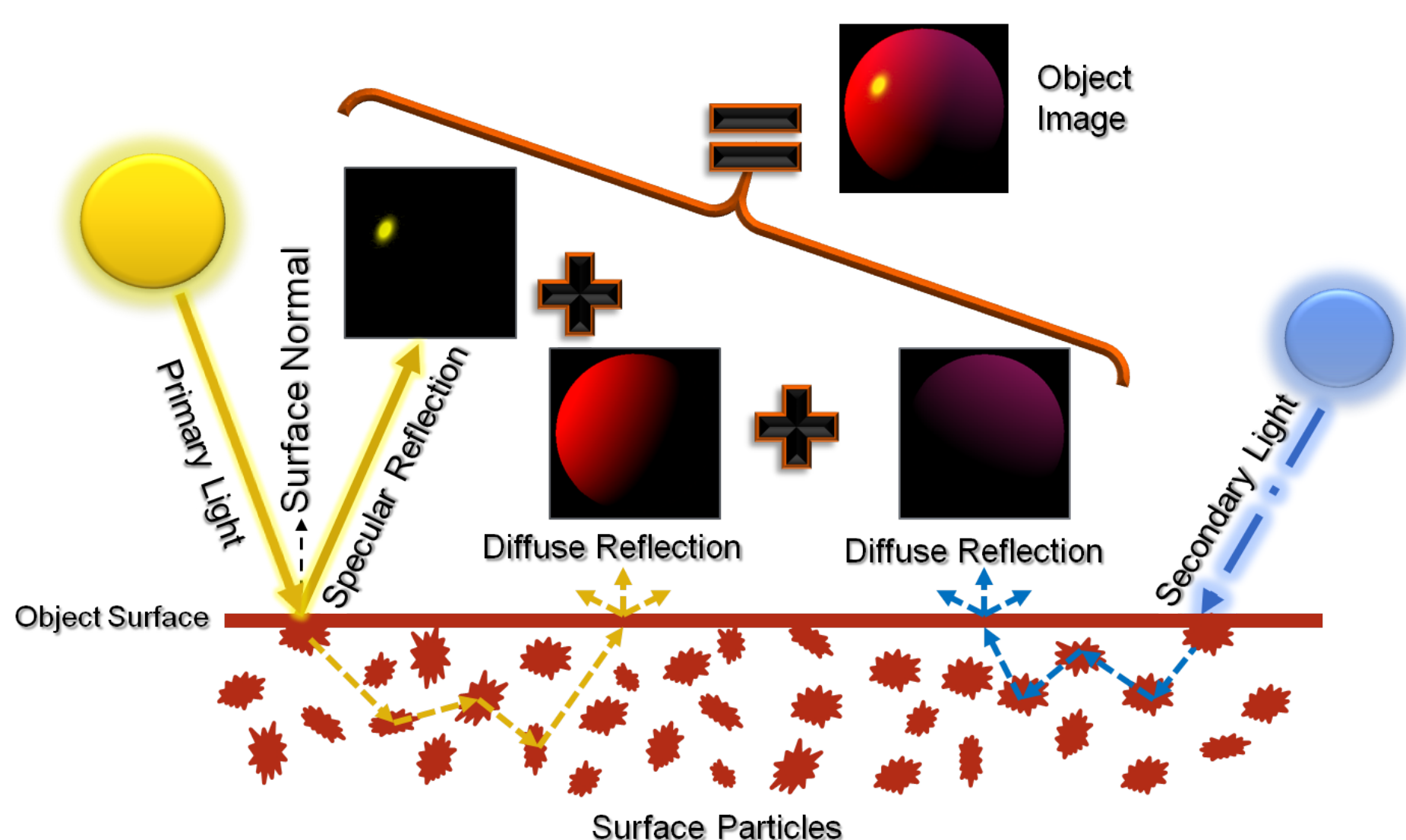
This equation can be divided into intrinsic images and the chromaticity of the object and illuminant in matrix notation. Where the intrinsic image matrix \mathbf{M} contains intrinsic images and the color characteristics matrix $\mathbf{C} = [\mathbf{L} \ \mathbf{c} \ \mathbf{l}]$ contains the relevant parameters for scene recoloring.

$$\mathbf{f} = [m_b(\mathbf{x}) \ m_s(\mathbf{x})] [\mathbf{L} \ \mathbf{c} \ \mathbf{l}]^T = \mathbf{M} \mathbf{C}^T, \quad (2)$$

MIDR

Real-world objects often exhibit body and surface reflection under more than just one illuminant (e.g., outdoor scene with blue sky and yellow sun). Here we extend the reflectance model to the Multi-Illuminant Dichromatic Reflection model(MIDR) to account for the secondary illuminants. The MIDR for n illuminants is given below.

$$\mathbf{f} = [\mathbf{M}^1 \dots \mathbf{M}^n] [\mathbf{C}^1 \dots \mathbf{C}^n]^T = \mathbf{M} \mathbf{C}^T, \quad (3)$$



Assumptions

- Single object with uniform albedo (non-chromatic textures are acceptable)
- Neutral interface reflectance
- Object presenting specularities
- Majority of the pixels are diffuse
- Object is lit by two illuminants with at least one being Planckian
- Sharp sensors (in practice we obtained good results on sensors which are not sharpened)
- Specularity of the secondary illuminant is negligible.

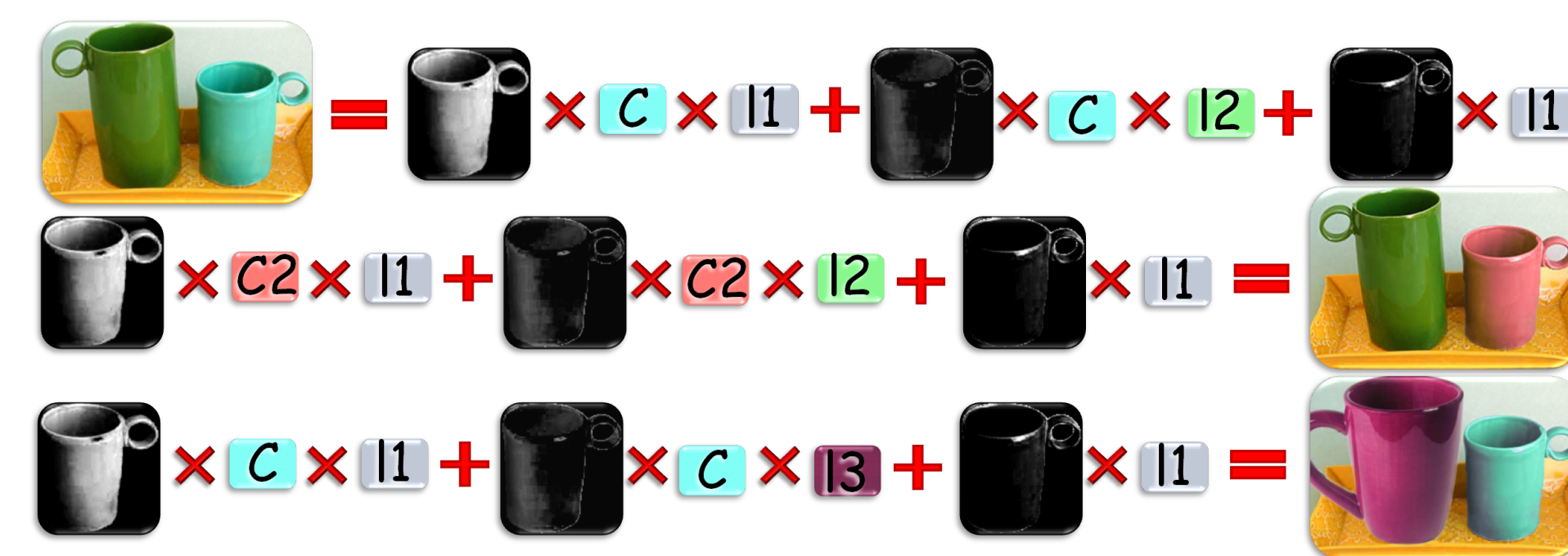
challenges

- Uncalibrated medium quality images
- Objects with complex shapes and specularities
- Complex lighting condition and Multiple illuminants

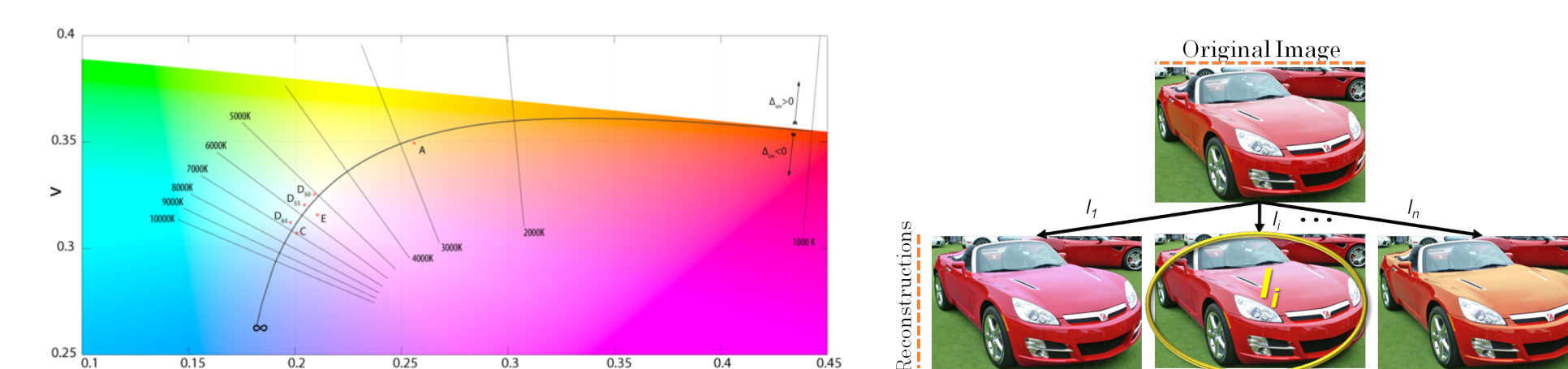
Two-illuminant MIDR model

The image below is a visualization of the two-illuminant MIDR decomposition, recoloring and photo-fusion respectively.

$$\mathbf{f} = m_b^1 \mathbf{c} \mathbf{L}^1 + m_s^1 \mathbf{l}^1 + m_b^2 \mathbf{c} \mathbf{L}^2. \quad (4)$$



Confined illuminants estimation (CIE)



Sampling Planckian colors ($T \subset 1000 \sim 40000$). We define the reconstruction error of the intrinsic images \mathbf{M} and intrinsic color characteristics \mathbf{C} by

$$E_r(\mathbf{f}, \mathbf{M}, \mathbf{C}) = (\mathbf{f} - \mathbf{M} \mathbf{C}^T)^T (\mathbf{f} - \mathbf{M} \mathbf{C}^T). \quad (5)$$

and choose the illuminant with minimal reconstruction error.

$$\hat{\mathbf{l}} = \arg \min_{\mathbf{l} \in \{\mathbf{l}_1, \dots, \mathbf{l}_m\}} E_r(\mathbf{f}, \mathbf{M}, [\mathbf{cL} \ \mathbf{l}]). \quad (6)$$

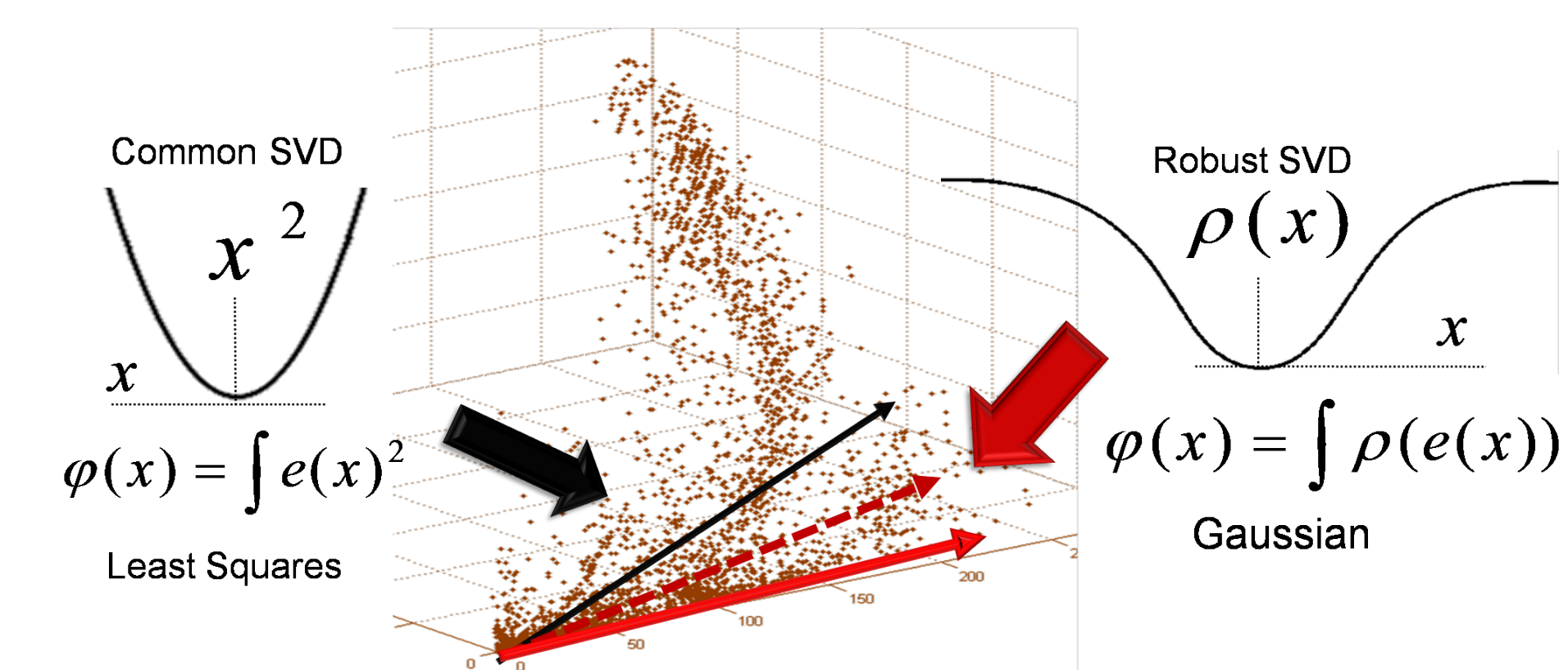
Robust Body Reflectance Estimation (RBRE)

Since object pixel values of the non-specular part ($m_s = 0$) form a line passing through the origin, fitting a line through these pixels allows us to compute $\mathbf{c}_b = \mathbf{cL}$, while e is the fitting error.

$$e(\mathbf{x}) = \|\mathbf{f}(\mathbf{x}) - ((\mathbf{f}(\mathbf{x}))^T \hat{\mathbf{c}}_b) \hat{\mathbf{c}}_b\|. \quad (7)$$

As here there are two main orientations (\mathbf{c}_b and \mathbf{l}), the least squares (LS) orientation estimation will mix the two orientations and give a wrong result. Therefore we use the following *robust estimator* in an iterative way to avoid that.

$$e = \int_{\Omega} \rho^m \left(\sqrt{\mathbf{f}^T \mathbf{f} - \hat{\mathbf{c}}_b^T (\mathbf{f} \mathbf{f}^T) \hat{\mathbf{c}}_b} \right) dx. \quad (8)$$



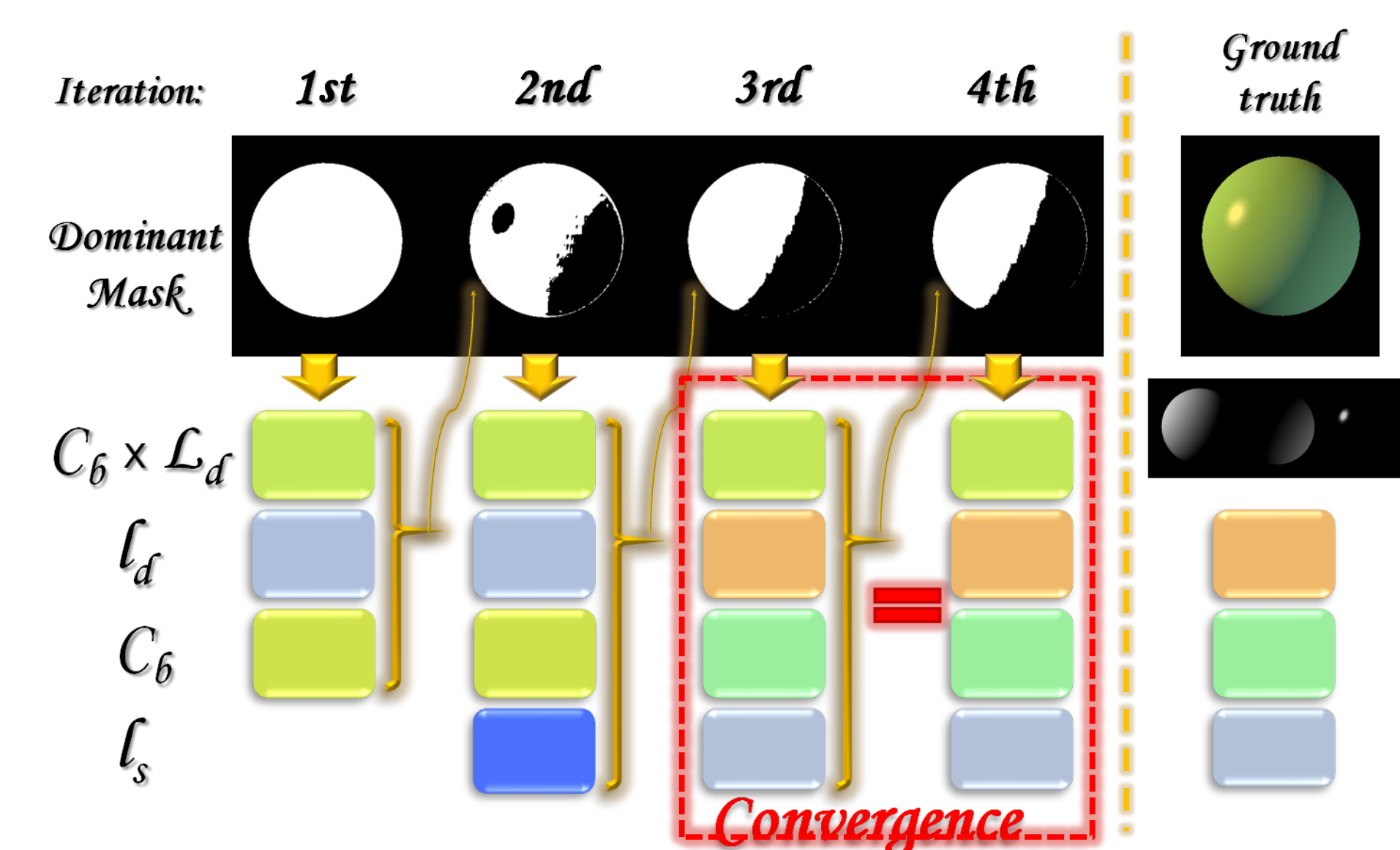
Intrinsic images

The estimation of the intrinsic images, given an estimation of $\hat{\mathbf{C}}$, is based on the convex optimization problem:

$$\begin{aligned} & \underset{\mathbf{M}}{\text{minimize}} E_r(\mathbf{f}, \mathbf{M}, \hat{\mathbf{C}}) \\ & \text{subject to } m_b(\mathbf{x}) \geq 0, m_s(\mathbf{x}) \geq 0. \end{aligned} \quad (9)$$

Algorithm

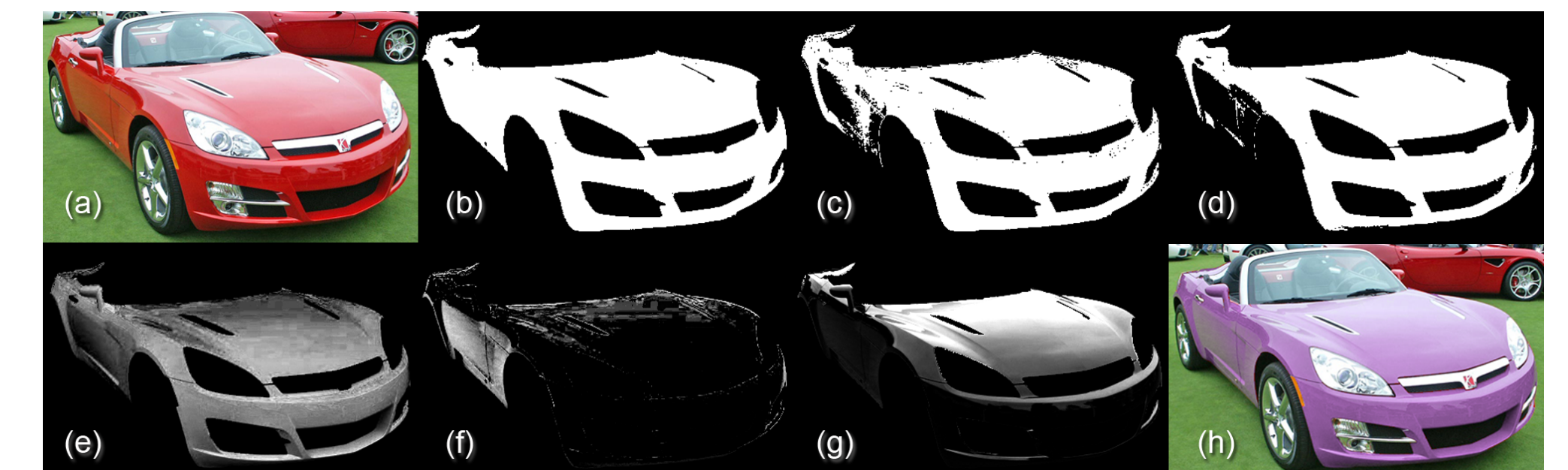
Below is a visualization of an example of the algorithm performance.



Project Page

<http://www.cat.uab.cat/~shida/Research/ObjectRecoloring>

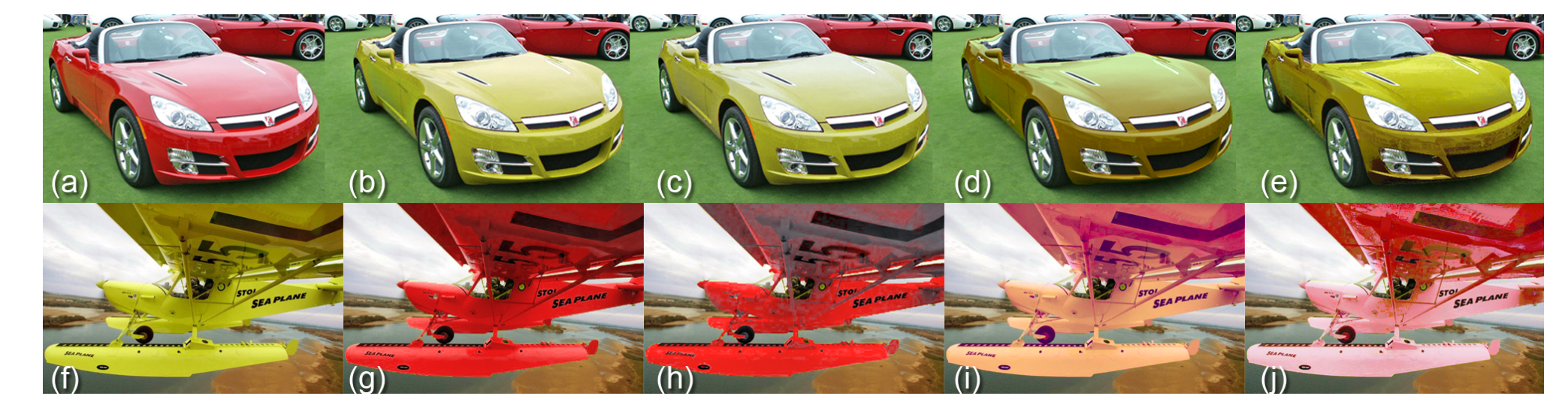
Results



An example of algorithm performance on a real-world image.



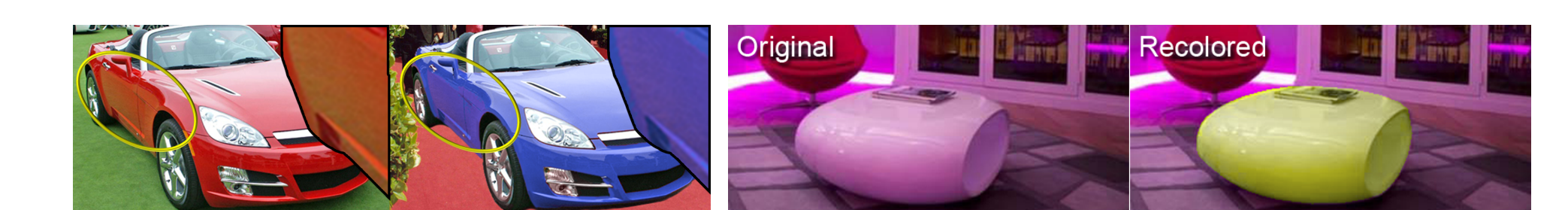
Examples of object recoloring while preserving the blueish ambient light and shadows.



Comparing *Color Transfer* results: MIDR (b & g), DRM (c & h), [2] (d & i), and [3] (e & j). Note that MIDR has correctly preserved the secondary illuminants (interreflections).



From left to right: Original image, recolored object, changing the primary illuminant, removing and recoloring the secondary illuminant.



Enhanced photo-fusion A failure case.

Conclusion

We presented a method to recolor objects taken under multiple colored illuminants based on intrinsic image estimation. We obtain physically realistic recoloring results on complex uncalibrated real-world images of medium quality. In addition we present how our method improves other photo-editing applications like *Color Transfer* and *Photo Fusion*.

Reference

- [1] A. Shafer and D. Lischinski. Using color to separate reflection components. *Color Research and Application*, 1985.
- [2] E. Reinhard, M. Ashikhmin, B. Gooch, and P. Shirley. Color transfer between images. *IEEE Computer Graphics and Applications*, 2001.
- [3] F. Pitić, A. C. Kokaram, and R. Dahyot. Automated colour grading using colour distribution transfer. *CVIU*, 2007.