Reflection Separation in Light Fields based on Sparse Coding and Specular Flow

Antonin Sulc, Anna Alperovich, Nico Marniok and Bastian Goldluecke
**Dichromatic model** assumption, color of each ray $r$ is sum of *specular* and *diffuse* terms

$$L(r) = \text{Specular}(r) + \text{Diffuse}(r) \quad (1)$$

[Shafer, CRA 1985]
**Dichromatic model** assumption, color of each ray \( r \) is sum of *specular* and *diffuse* terms

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L(r) = \text{Specular}(r) + \text{Diffuse}(r) \tag{1}
\]

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**Dichromatic model** assumption, color of each ray $r$ is sum of *specular* and *diffuse* terms

$$L(r) = \text{Specular}(r) + \text{Diffuse}(r)$$  \hspace{1cm} (1)

[Shafer, CRA 1985]

1. **Single light source**
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L(r) = \text{Specular}(r) + \text{Diffuse}(r)
\]  \hspace{1cm} (1)

[Shafer, CRA 1985]

1. **Single light source**
2. **Dielectric material:**

\[
\text{Specular}(r) = S_c \sigma (r)
\]  \hspace{1cm} (2)
**Image formation model**

- **Dichromatic model** assumption, color of each ray $r$ is sum of *specular* and *diffuse* terms

\[ L(r) = \text{Specular}(r) + \text{Diffuse}(r) \]  

[Shafer, CRA 1985]

1. **Single light source**
2. **Dielectric material:**

\[ \text{Specular}(r) = S_c \sigma(r) \]  

3. **Finite and fixed set of $K$ albedos** $D = (A_1, \ldots, A_K)$,

\[ \text{Diffuse}(r) = A_1 \alpha_1(r) + \cdots + A_K \alpha_K(r) \]
The image formation can be formulated as Non-Negative Matrix Factorization (NMF)

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Non-Negative Factorization

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\[
= S_c \sigma(r) + \sum_{k=1}^{K} A_k \alpha_k(r)
\]

\[
= S_c \sigma(r) + D\alpha(r)
\]
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\[ = S_c \sigma(r) + \sum_{k=1}^{K} A_k \alpha_k(r) \]

\[ = S_c \sigma(r) + D\alpha(r) \quad (4) \]

**Idea** Use as few albedos as possible
The image formation can be formulated as Non-Negative Matrix Factorization (NMF)

\[ L(\mathbf{r}) = \text{Specular}(\mathbf{r}) + \text{Diffuse}(\mathbf{r}) = S_c \sigma(\mathbf{r}) + \sum_{k=1}^{K} A_k \alpha_k(\mathbf{r}) = S_c \sigma(\mathbf{r}) + D\alpha(\mathbf{r}) \]  

**Idea** Use as few albedos as possible

Sparsity is enforced by \( \| \cdot \|_1 \) norm on \( \alpha \) and \( \sigma \):

\[
\arg\min_{D,\alpha} \lambda_s \| \sigma \|_1 + \lambda_d \| \alpha \|_1 + \| L - S_c \sigma - D\alpha \|_2^2
\]  

[Akashi and Okatani, ACCV 2014]
Our contributions

We extended the original NMF approach
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\[
\arg\min_{\alpha} \lambda_s \|\sigma\|_1 + \lambda_d \|\alpha\|_1 + \|L - S_c\sigma - D\alpha\|_2^2
\]

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Light field anisotropic diffuse regularizer \([GW13]\) +

Light field anisotropic specular regularizer for specular motion
Our contributions

We extended the original NMF approach

\[
\arg \min_{\alpha} \lambda_s \|\sigma\|_1 + \lambda_d \|\alpha\|_1 + \|L - S_c\sigma - D\alpha\|_2^2 + R_d(\alpha)
\]

Light field anisotropic diffuse regularizer [GW13]
Our contributions

We extended the original NMF approach

\[
\arg\min_{\alpha} \lambda_s \| \sigma \|_1 + \lambda_d \| \alpha \|_1 + \| L - S_c \sigma - D \alpha \|_2^2 \\
+ \\
R_d(\alpha) \\
\text{Light field anisotropic diffuse regularizer [GW13]} \\
+ \\
R_s(\sigma) \\
\text{Novel Light field anisotropic specular regularizer for specular motion}
\]
Light fields
A 2D horizontal cut (green) is called an **epipolar plane image (EPI)**

\[(u, v) \rightarrow (u, v, s, t)\]

[Wanner and Goldluecke, CVPR 2012 & TPAMI 2014]
Light-fields and specular surfaces

$L(u, v, s, t)$

$L(u, v, s+1, t)$
A Lambertian 3D point has the same color in all views.

Disparity $d$ is the displacement of the two projections of a 3D point between two consecutive views.

Color along $[d; 1]^T$ should be constant in $u_{ty}$ and $u_{sx}$.
Anisotropic regularizer $J_v$ encourages constancy in direction of vector field $v = [d; 1]^T$ for every component $e_i$ of the EPI $e$

$$J_v (e) = \sum_{i=1} \int_{\text{dom}(e)} \sqrt{\nabla e_i^T (vv^T) \nabla e_i} \, dp$$  \hspace{1cm} (6)$$

[Goldluecke and Wanner CVPR 2013]
Regularization on the complete light field

Two EPIs, horizontal $u_{ty}$ and vertical $u_{sx}$

$$J_d (\alpha) = \int J_{[1 \ d]}^T (\alpha_{s,x}) \ d (s, x) \quad \text{/ / vertical EPI}$$
Two EPIs, horizontal $\mathbf{u}_{ty}$ and vertical $\mathbf{u}_{sx}$

\[ \begin{align*}
J_d (\alpha) &= \int J_{[1 \ 0]}^T (\alpha_{s,x}) \, d(s, x) \quad \text{// vertical EPI} \\
&+ \int J_{[0 \ 1]}^T (\alpha_{t,y}) \, d(t, y) \quad \text{// horizontal EPI}
\end{align*} \]
Reflection follows different motion, **specular flow**
The motion of specularities

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- Specular flow depends on **surface curvature**
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- Reflection follows different motion, **specular flow**
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\[ \hat{r} \]

\[ \hat{C} \]

Motion $\rightarrow$ Geometry  
Geometry $\rightarrow$ Motion

[Adato, Vasilyev, Shahar and Zickler, ICCV 2007]
Computation of specular flow

Disparity map $d$

Specular flow $(w_{s,x}, w_{s,y})$

1. Calculate depth map from disparity $d$ for a calibrated camera
2. Calculate surface curvature $C$
3. Given baseline and curvature $(C)$ we can infer specular flow
   - Move **horizontally**, we obtain specular flow $w_s = (w_{s,x}, w_{s,y})$
   - Move **vertically**, we obtain specular flow $w_t = (w_{t,x}, w_{t,y})$
**Idea** The regularization direction is parallel to the individual EPIs
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\[
\int J_{[1\ d]}^T (\alpha_{s,x}) \, d(s,x) = \int J_{[1\ d\ 0]}^T (\alpha_s) \, ds \\
\int J_{[1\ d]}^T (\alpha_{t,y}) \, d(t,y) = \int J_{[1\ 0\ d]}^T (\alpha_t) \, dt
\] (8)

Regularization on **epipolar plane volume** is about ten times faster compared to sum over all 2D EPIs.
Regularization of specular components $J_s$

\[ \int J_{[1,w_{t,x},w_{t,y}]}^T (\sigma_t) \, dt \]
\[ \int J_{[1,w_{s,x},w_{s,y}]}^T (\sigma_s) \, ds \]
Final energy

\[
\arg\min_{u=\{\sigma, \alpha\}} \int E(u(r), D) \, dr + \text{//sparsity + data term}
\]
Final energy

$$\arg\min_{u=[\sigma,\alpha]} \int E(u(r), D) dr + \mu_d J_d(\alpha) + \mu_s J_s(\sigma) + \rho_d \int ITGV_2(\sigma_s, t) ds dt + \rho_s \int ITGV_2(\sigma_s, t) ds dt + \text{// sparsity + data term} + \text{// diffuse volume}$$
Final energy

\[
\arg\min_{u=[\sigma, \alpha]} \int E(u(r), D) \, dr + //\text{sparserity + data term}
\]

\[
\mu_d J_d (\alpha) + //\text{diffuse volume}
\]

\[
\mu_s J_s (\sigma) + //\text{specular volume}
\]
Final energy

\[
\arg\min_{u=[\sigma, \alpha]} \int E(u(r), D) \, dr + \frac{1}{\rho_d} \int \operatorname{ITGV}_2(\alpha_{s,t}) \, d(s, t) + \frac{1}{\mu_d} J_d(\alpha) + \frac{1}{\mu_s} J_s(\sigma) + \text{// sparsity + data term} \\
+ \text{// diffuse volume} \quad + \text{// specular volume} \quad + \text{// diffuse spatial}
\]
Final energy

\[
\text{arg min}_{\mathbf{u}=[\sigma,\alpha]} \int E(\mathbf{u}(\mathbf{r}), D) \, d\mathbf{r} + \text{//sparsity + data term}
\]

\[
\mu_d J_d (\alpha) + \text{// diffuse volume}
\]

\[
\mu_s J_s (\sigma) + \text{// specular volume}
\]

\[
\rho_d \int \text{ITGV}_2 (\alpha_s, t) \, d(s, t) + \text{// diffuse spatial}
\]

\[
\rho_s \int \text{ITGV}_2 (\sigma_s, t) \, d(s, t) + \text{// specular spatial}
\]
**Initialize** Dictionary $D$, and sparse coefficients $\alpha, \sigma$,

- precalculate light source color $S_c$,

[Yang, Gao and Li, ICCV 2015]
Optimization

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- precalculate light source color $S_c$,
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- precalculate disparity map $d$.
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- precalculate orientation for $J_d(\alpha)$ and $J_s(\sigma)$
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Iterate  Update $\alpha$ and $\sigma$ with gradient descent of  
$\|L - S_c\sigma + D\alpha\|^2_2$.
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**Iterate**

- Update $\alpha$ and $\sigma$ with gradient descent of
  
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- Update $\alpha$ and $\sigma$ with subgradient descent for
  sparsity norm.
**Initialize**  Dictionary $D$, and sparse coefficients $\alpha$, $\sigma$,

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- precalculate orientation for $J_d(\alpha)$ and $J_s(\sigma)$

**Iterate**  Update $\alpha$ and $\sigma$ with gradient descent of

\[ \| L - S_c \sigma + D\alpha \|^2_2. \]

- Update $\alpha$ and $\sigma$ with subgradient descent for sparsity norm.

- Update $\alpha$ and $\sigma$ with subgradient descent of diffuse and sparsity regularizer $J_d(\alpha)$ and $J_s(\sigma)$. 
Optimization

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**Iterate**
- Update $\alpha$ and $\sigma$ with gradient descent of $\|L - S_c\sigma + D\alpha\|_2^2$.
- Update $\alpha$ and $\sigma$ with subgradient descent for sparsity norm.
- Update $\alpha$ and $\sigma$ with subgradient descent of diffuse and sparsity regularizer $J_d(\alpha)$ and $J_s(\sigma)$.
- Update $\alpha_{s,t}$ and $\sigma_{s,t}$ for every subaperture view $(s, t)$ with TGV.
Optimization

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- Update $\alpha$ and $\sigma$ with gradient descent of
  
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- Update $\alpha_{s,t}$ and $\sigma_{s,t}$ for every subaperture view $(s, t)$ with TGV.
Results
Reflection Separation in Light Fields

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Input

Ours Single view [AO14] Tao et al. [TSW*15]

Diffuse

Specular
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Conclusion

1. We extend the original pixel-wise approach for reflection separation to 4D light fields.

2. Just like the original approach, we assume dichromatic model and a sparse linear combination of a finite set of albedos.

3. In addition, we regularize the diffuse component with the light-field based approach [GW13].

4. Furthermore, we introduce a novel anisotropic regularizer for specular components based on specular flow field.

5. We outperform the single image model [AO14] and previous light fields based approach [TSW*15].