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

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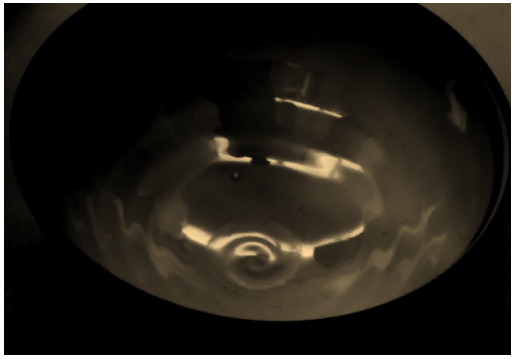

Image formation model

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

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

[Shafer, CRA 1985]

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1 Single light source

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

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$$\text{Specular}(\mathbf{r}) = S_c \sigma(\mathbf{r}) \tag{2}$$

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

$$\text{Diffuse}(\mathbf{r}) = A_1 \alpha_1(\mathbf{r}) + \cdots + A_K \alpha_K(\mathbf{r}) \tag{3}$$

Non-Negative Factorization

- The image formation can be formulated as Non-Negative Matrix Factorization (NMF)

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- Sparsity is enforced by $\|\cdot\|_1$ norm on $\boldsymbol{\alpha}$ and σ:

$$\arg\min_{D,\alpha} \lambda_s \|\sigma\|_1 + \lambda_d \|\boldsymbol{\alpha}\|_1 + \|L - S_c\sigma - D\boldsymbol{\alpha}\|_2^2 \tag{5}$$

[Akashi and Okatani, ACCV 2014]

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$$\underbrace{\mathrm{R}_d\left(\boldsymbol{\alpha}\right)}_{\text{Light field anisotropic diffuse regularizer [GW13]}}$$

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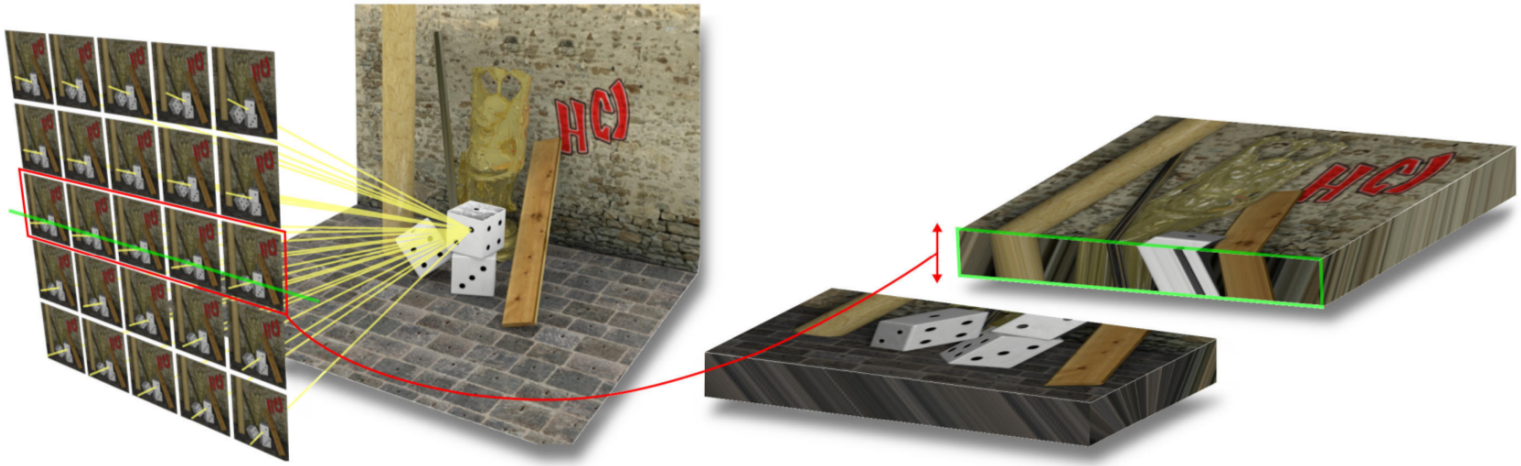
$$+$$

$$\underbrace{\mathrm{R}_s(\sigma)}_{\textbf{Novel}\text{ Light field anisotropic specular regularizer for specular motion}}$$

Light fields

The light field as a dense collection of views



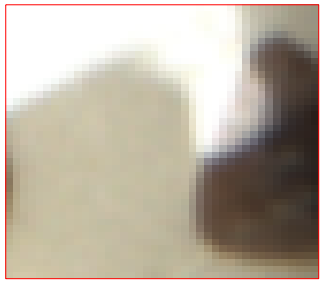
A 2D horizontal cut (green) is called an **epipolar plane image (EPI)**

[Wanner and Goldluecke, CVPR 2012 & TPAMI 2014]

$$(u, v) \rightarrow (u, v, s, t)$$

Light-fields and specular surfaces

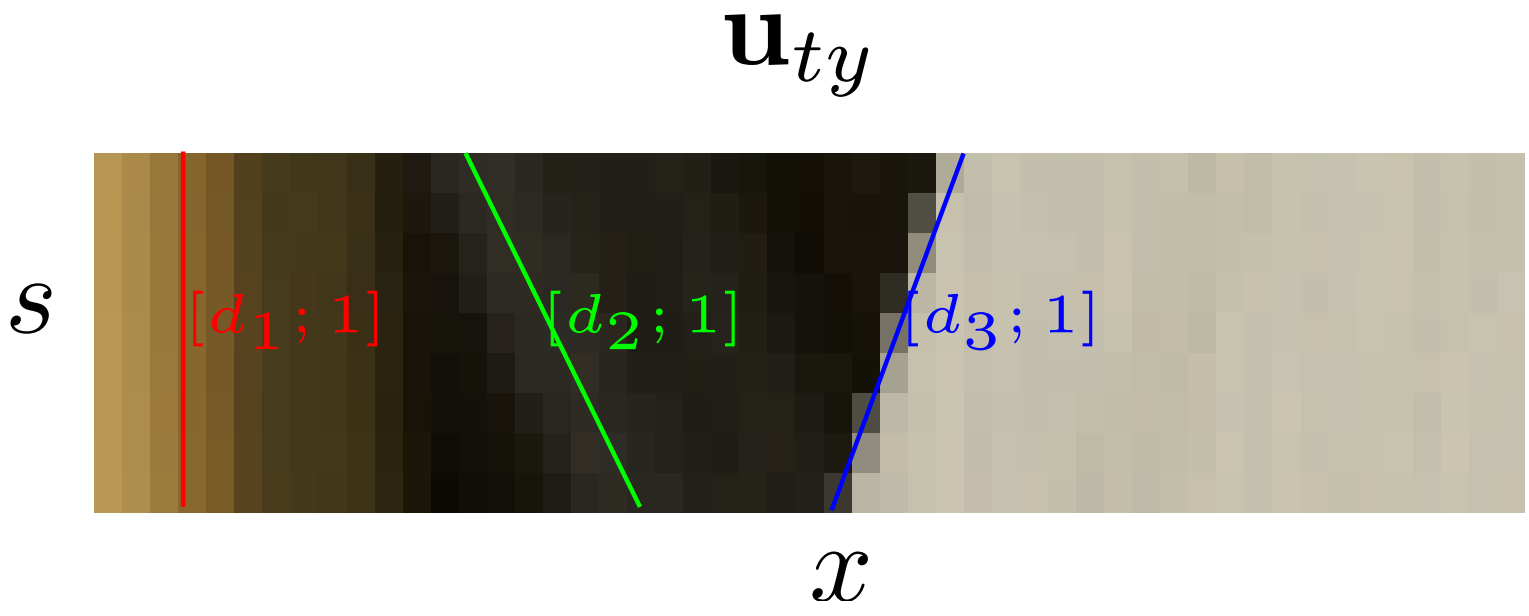
$L(u, v, s, t)$ $L(u, v, s+1, t)$



EPI structure for diffuse components

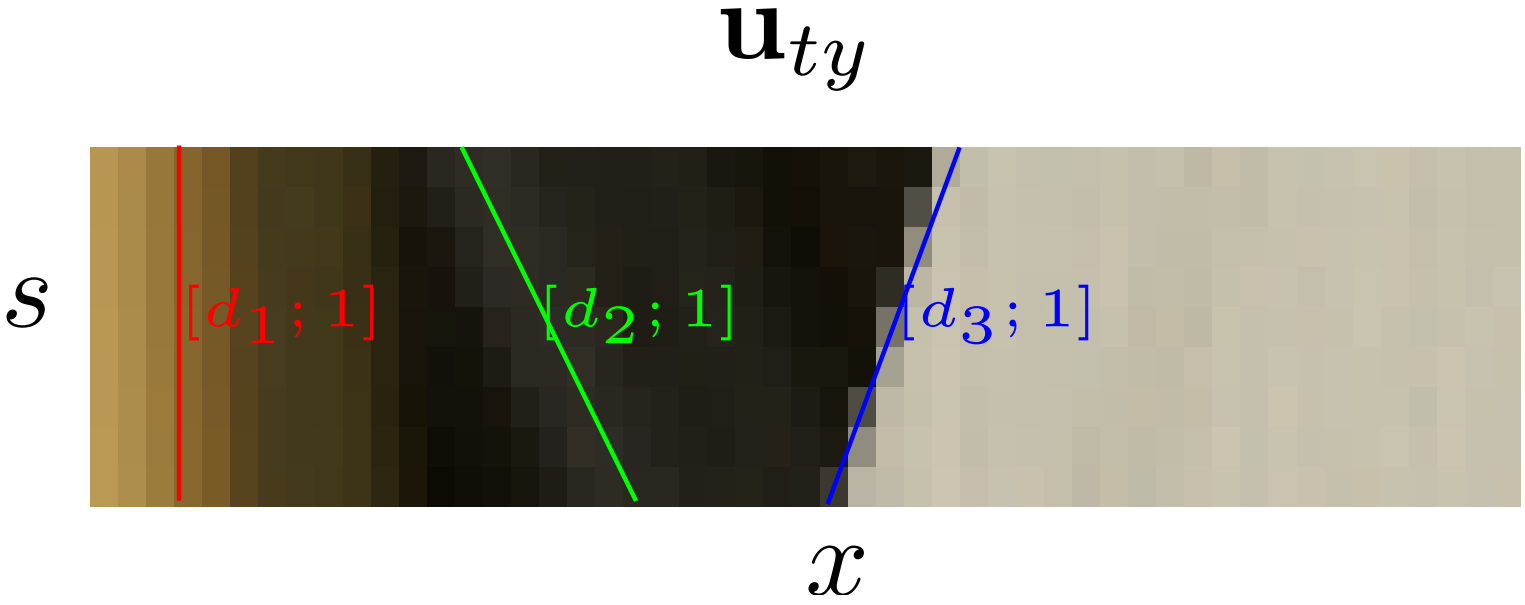
- A Lambertian 3D point has the same color in all views.
- Disparity d is the displacement of the two projections of a 3D point between two consecutive views.

Color along $[d; 1]^T$ should be constant in $\mathbf{u}_{ty}$ and $\mathbf{u}_{sx}$.



[Goldluecke and Wanner CVPR 2013]

Regularization of the diffuse components



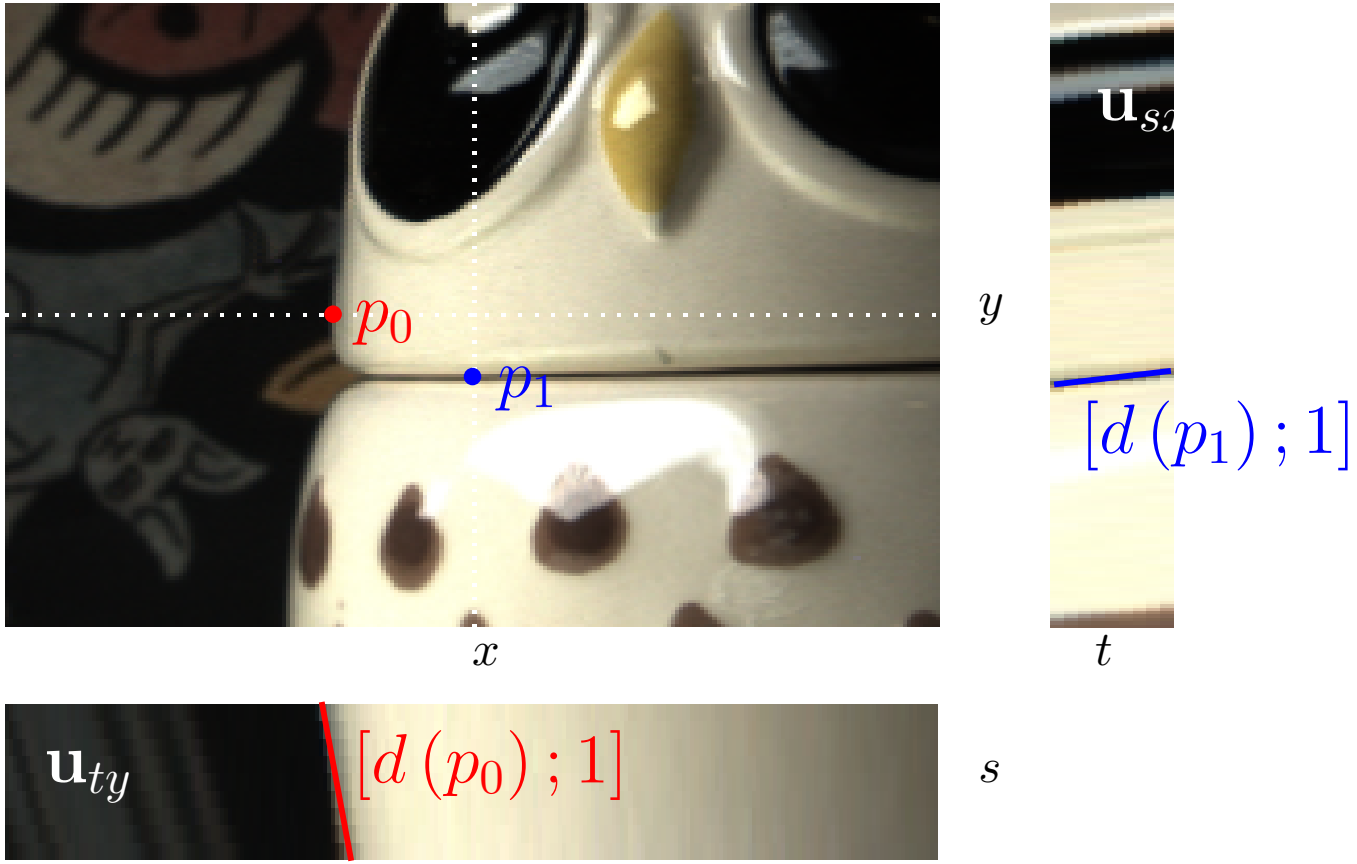
Anisotropic regularizer J_v encourages constancy in direction of vector field $\mathbf{v} = [d; 1]^T$ for every component $\mathbf{e}_i$ of the EPI $\mathbf{e}$

$$J_v(\mathbf{e}) = \sum_{i=1} \int_{\mathrm{dom}(\mathbf{e})} \sqrt{\nabla \mathbf{e}_i^T \left(\mathbf{v}\mathbf{v}^T\right) \nabla \mathbf{e}_i} d\mathbf{p} \tag{6}$$

[Goldluecke and Wanner CVPR 2013]

Regularization on the complete light field

Two EPIs, horizontal $\mathbf{u}_{ty}$ and vertical $\mathbf{u}_{sx}$



$$J_d(\alpha) = \int J_{[1\ d]^T}(\boldsymbol{\alpha}_{s,x})\, d(s,x) \quad // \text{ vertical EPI}$$

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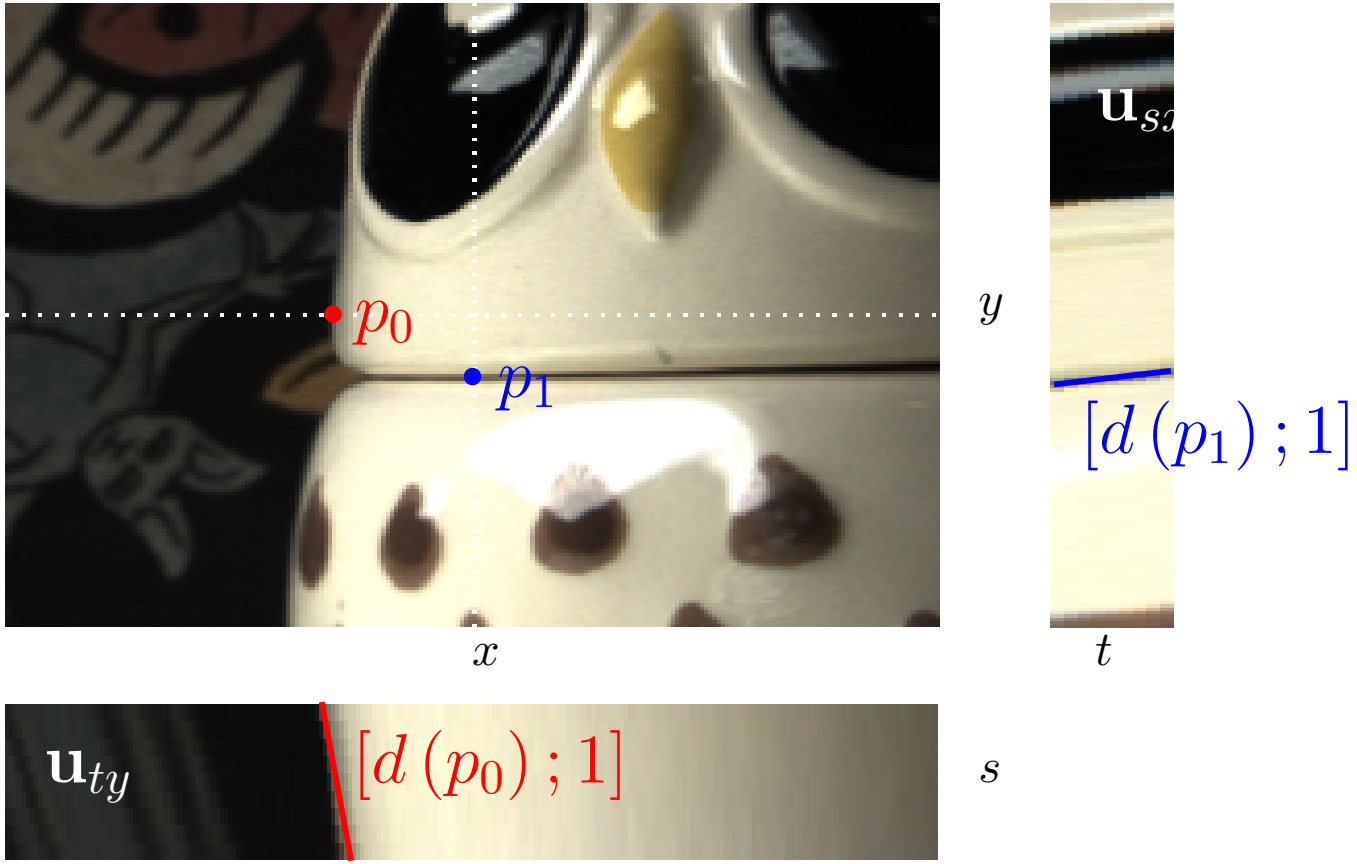

$$
\begin{aligned}
J_d(\alpha) &= \int J_{[1\ d]^T}(\boldsymbol{\alpha}_{s,x})\, d(s,x) && // \text{ vertical EPI} \\
&+ \int J_{[1\ d]^T}(\boldsymbol{\alpha}_{t,y})\, d(t,y) && // \text{ horizontal EPI}
\end{aligned}
\tag{7}
$$

[Goldluecke and Wanner CVPR 2013]

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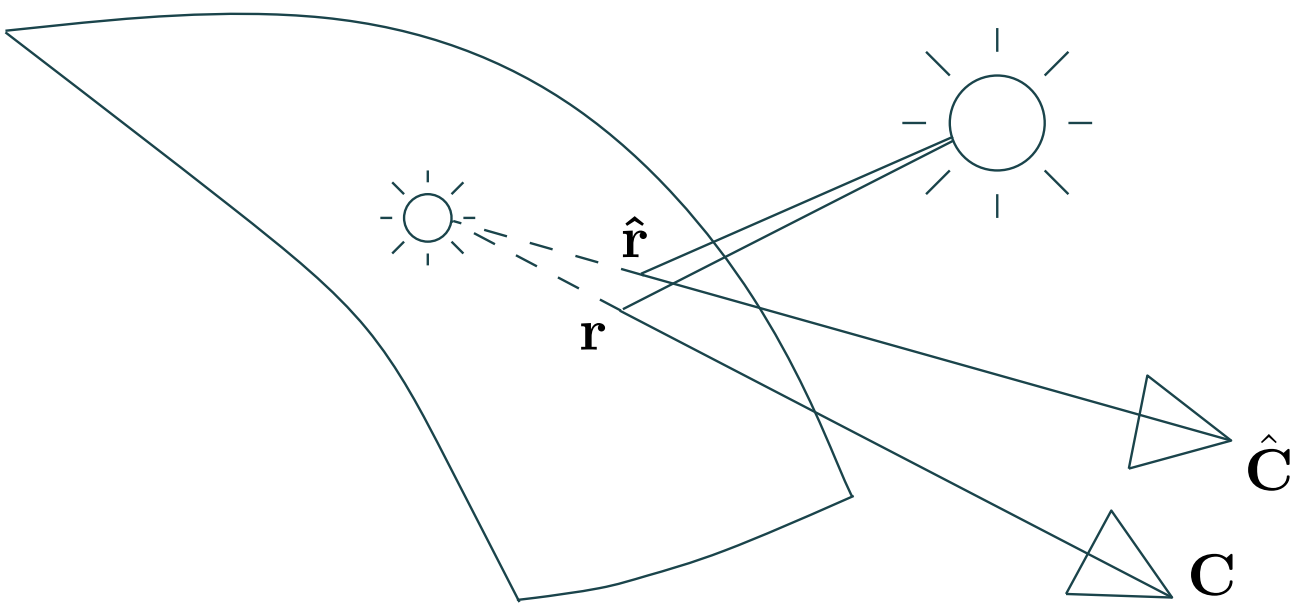

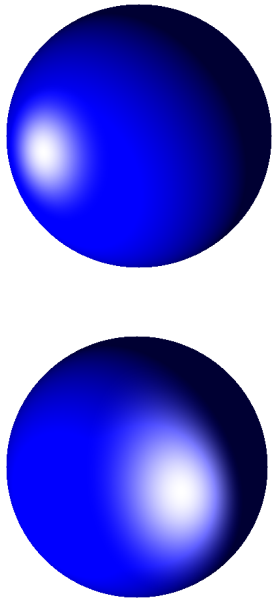

The motion of specularities

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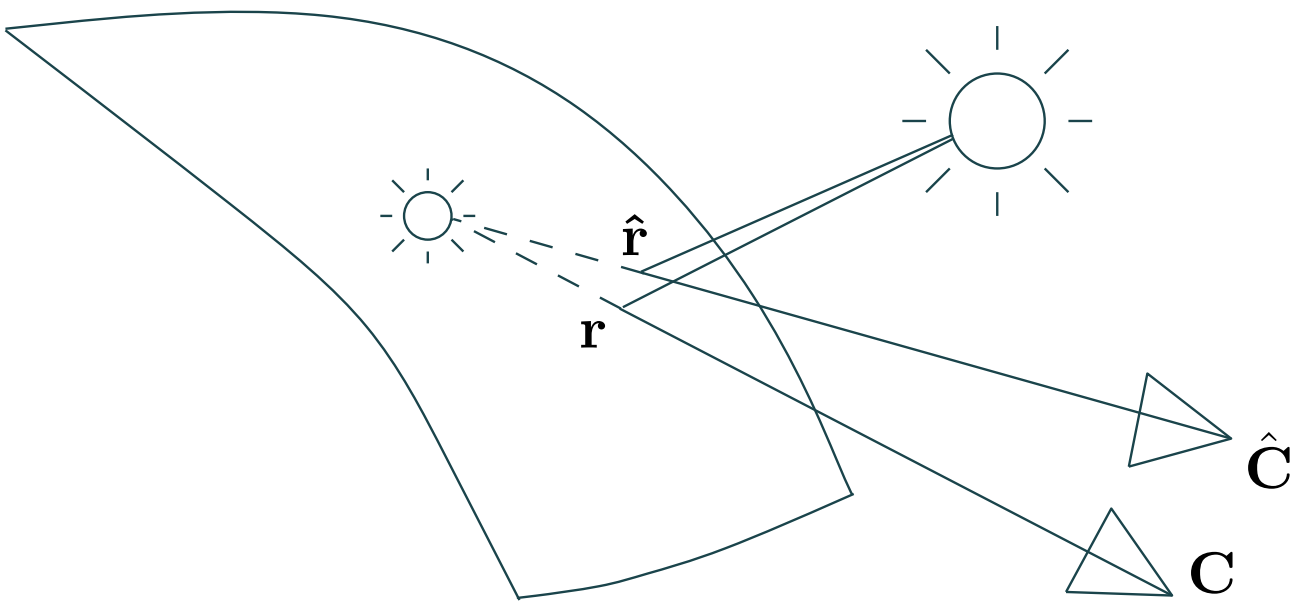

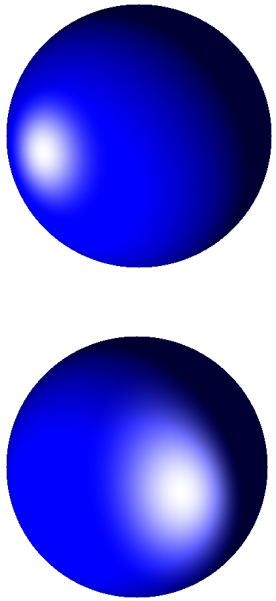

Motion $\rightarrow$ Geometry

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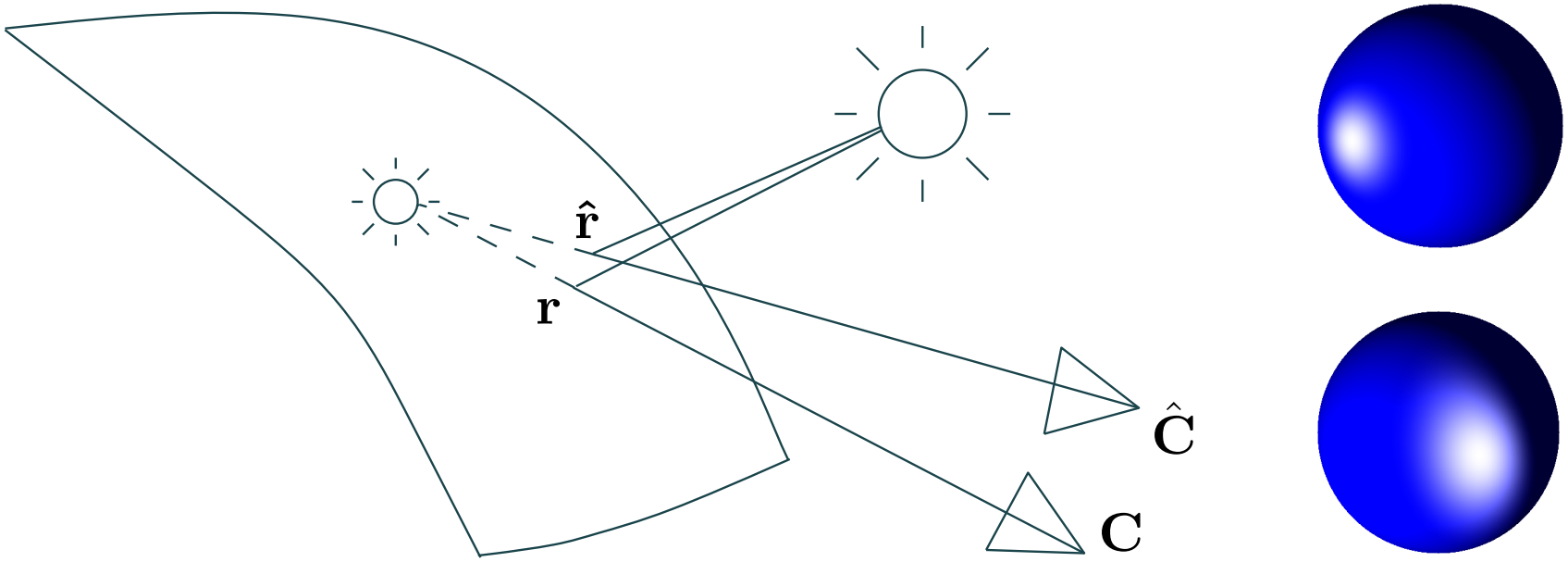
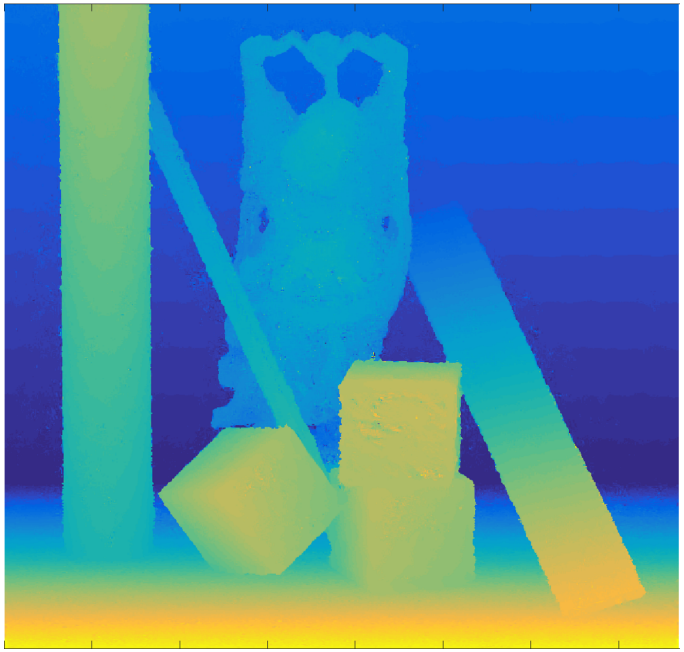


Motion → Geometry | **Geometry → Motion**

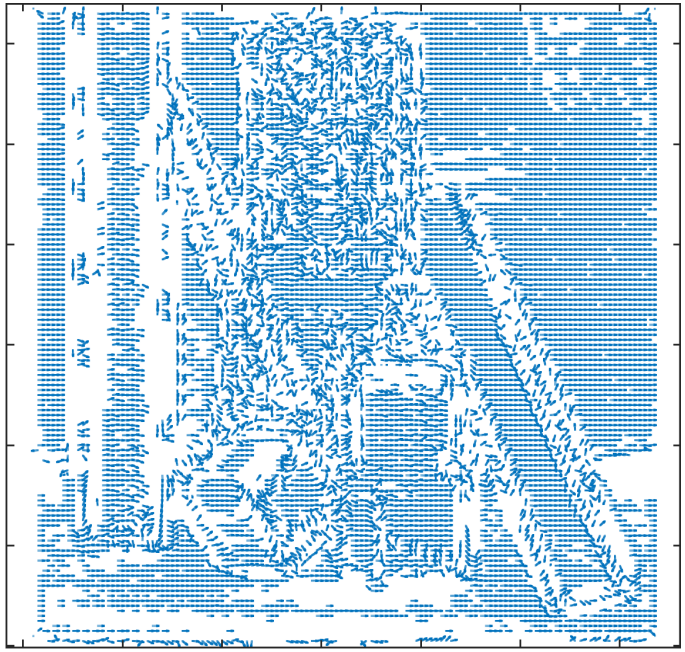
[Adato, Vasilyev, Shahar and Zickler, ICCV 2007]

Computation of specular flow

Disparity map d



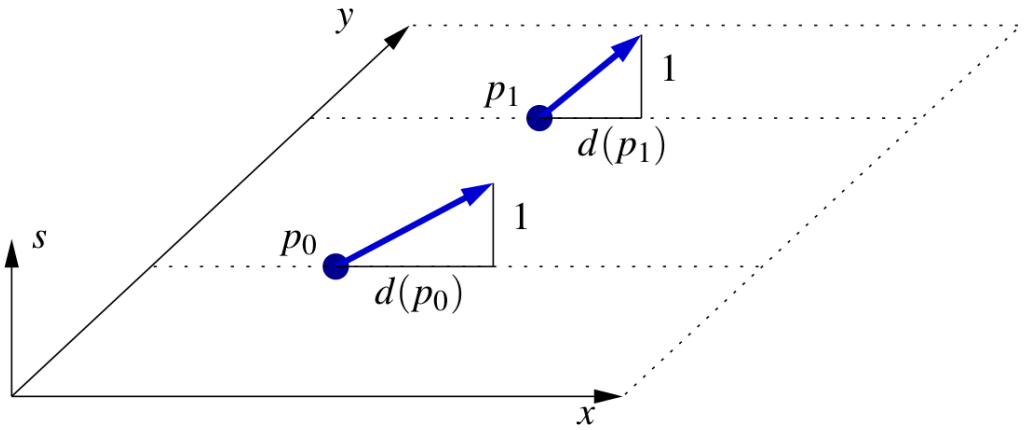
Specular flow $(w_{s,x}, w_{s,y})$



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 $\mathbf{w}_s = (w_{s,x}, w_{s,y})$
   - Move **vertically**, we obtain specular flow $\mathbf{w}_t = (w_{t,x}, w_{t,y})$

Regularization of diffuse components J_d

Idea The regularization direction is parallel to the individual EPIs



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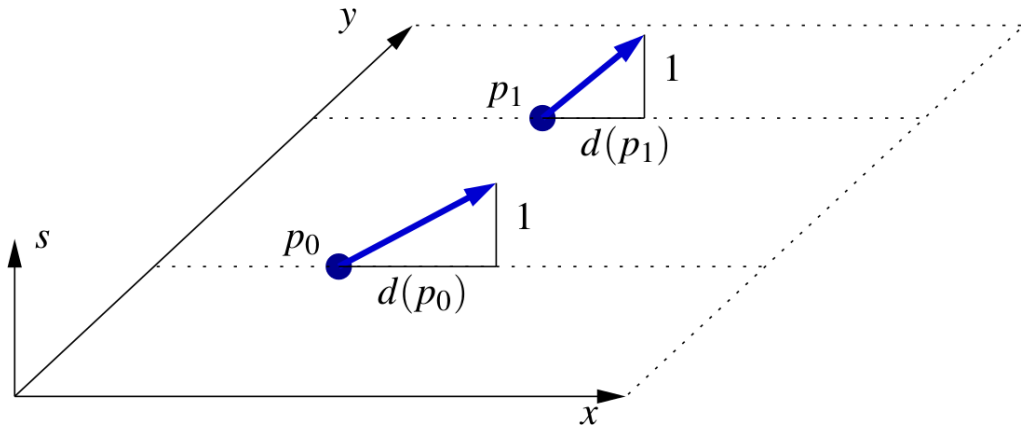
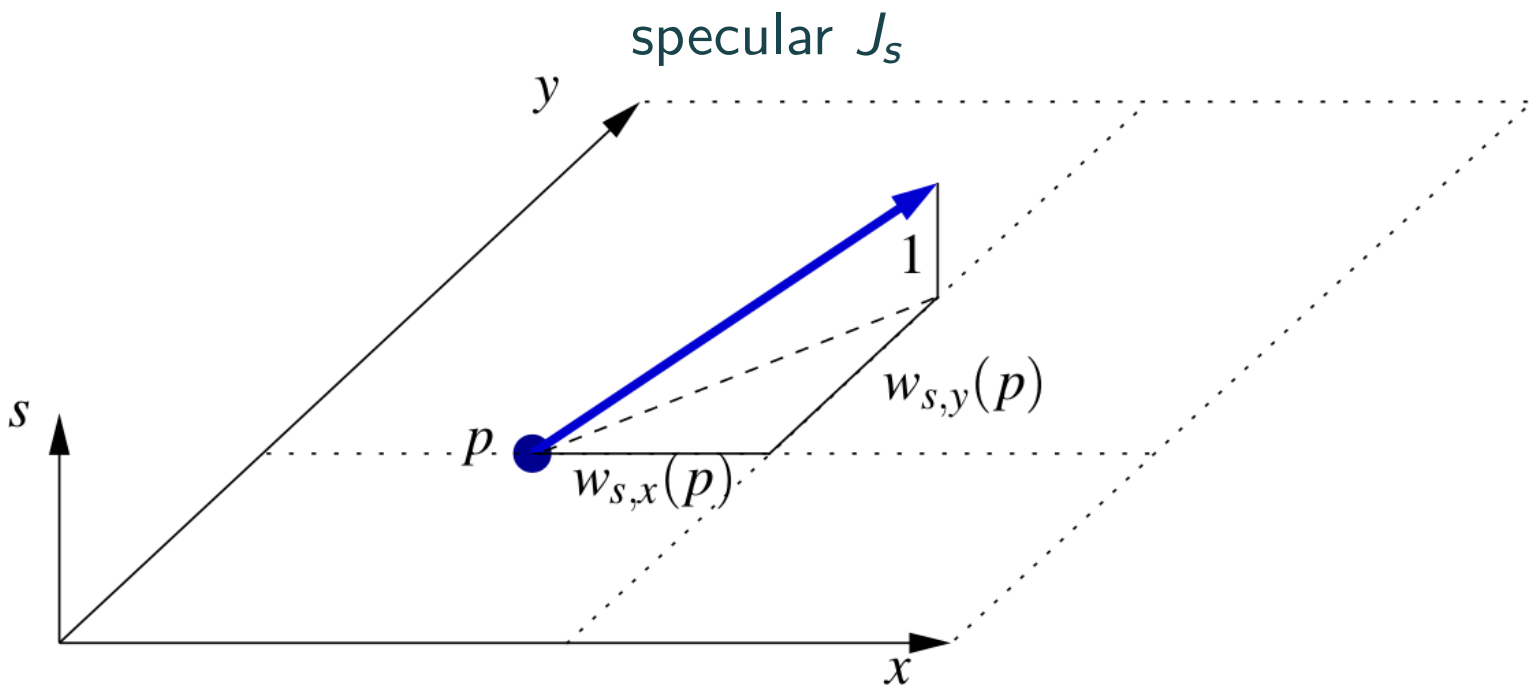


$$\begin{aligned} \int J_{[1\ d]^T}(\boldsymbol{\alpha}_{s,x})\, d(s,x) &= \int J_{[1\ d\ 0]^T}(\boldsymbol{\alpha}_s)\, ds \\ \int J_{[1\ d]^T}(\boldsymbol{\alpha}_{t,y})\, d(t,y) &= \int J_{[1\ 0\ d]^T}(\boldsymbol{\alpha}_t)\, dt \end{aligned} \tag{8}$$

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

$$\underset{\mathbf{u}=[\sigma,\alpha]}{\arg\min} \quad \int E\left(\mathbf{u}\left(\mathbf{r}\right), D\right) d\mathbf{r} \quad + \quad //\textit{sparsity} + \textit{data term}$$

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$$\mu_d J_d\left(\boldsymbol{\alpha}\right) \quad + \quad \textit{// diffuse volume}$$

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& \rho_d \int \mathrm{ITGV}_2\left(\boldsymbol{\alpha}_{s,t}\right) d\left(s,t\right) && + \quad \textit{// diffuse spatial}
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Optimization

Initialize Dictionary D, and sparse coefficients $\boldsymbol{\alpha}, \sigma$,

- precalculate light source color S_c,

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- Update $\boldsymbol{\alpha}$ and σ with gradient descent of $\|L - S_c\sigma + D\boldsymbol{\alpha}\|_2^2$.

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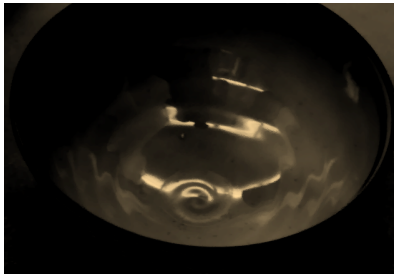
Results

Input

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

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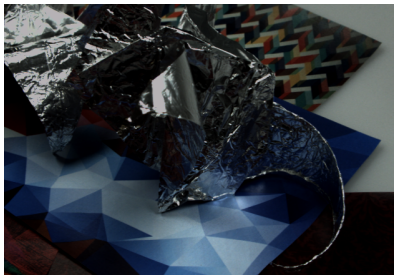
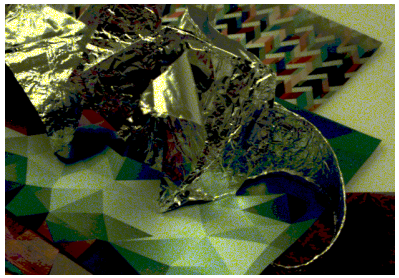
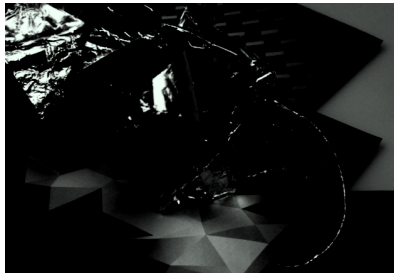
Diffuse			
Specular			

Input

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Diffuse			
Specular			

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].